ERASMUS UNIVERSITEIT ROTTERDAM
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Master Thesis Industrial Dynamics and Strategy

Platform revolution in healthcare: the role of information asymmetries on medication expenditure

In this thesis, the impact a platform business model can have on the healthcare sector is examined. Firstly, the study elaborates on the mechanics and benefits of the platform business model as well as on the reasons why the healthcare sector has yet to be revolutionised by platforms, before narrowing down to the case of e-pharmacy '1mg' operating in the troubled Indian pharmaceutical industry. Subsequently, the effect of decreased information asymmetries regarding brand substitution on medicine expenditure is analysed using a fixed effects regression and descriptive evidence. The results show that the decrease of the information asymmetry regarding alternative brands and possible price savings realised by 1mg do not lead to users substituting towards less costly medicine brands. This study contributes the lack of price saving substitutions to a dearth of freedom for patients to purchase brands of their choosing, stemming from inapt regulations and institutional voids. Therefore, the study concludes with policy recommendations directed at releasing the full potential of e-pharmacy enabled decreases in medication expenditure.

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1. Introduction

1.1 The emergence of platform business models globally and in healthcare

In today's world, platform based interactions have become an essential part of everyday life. Whether you are looking for a quick and cheap taxi ride, accommodation for a trip abroad, your favourite music or even a job, there are multiple apps by platform businesses that cater to your every need (e.g. Uber, AirBnB, Spotify and Upwork). The platform business model can be defined as: "… a business based on enabling value-creating interactions between external producers and consumers." (Parker, Van Alstyne, & Choudary, 2016), meaning that a platform merely *facilitates* interactions to take place, while claiming a portion of the interaction's value. Platforms are not new; the very first marketplace ever could be considered a platform, in the sense that it brought together sellers of produce and their buyers in one central place. A more modern example would be an auction house; facilitating a physical platform (the auction house itself) where artists and art-collectors can meet and sell or buy art, while the arthouse charges a fee for each transaction.

However, the development that enabled the platform business model to take the world by storm the past decade and disrupt many, previously considered sturdy markets, is the Digital Revolution. The emergence and rapid penetration of the internet coupled with the transition to the Age of Information, has allowed platforms to facilitate interactions online and change everyday life around the globe significantly. By making use of the merits of instant communication and the massive amounts of data generated by digitizing transactions, many industries have seen new players greatly increasing efficiency by aggregating both sides of the market, adopting a facilitating position between parties while eliminating intermediaries, and de-linking assets from value (Parker, Van Alstyne, & Choudary, 2016). With these strategies, "new kids on the block" have been able to dwarf many sectors' big incumbents in a matter of years .

Nonetheless, not every industry has proven to be as easily conquered by platform business models. Industry characteristics complicating disruption by platforms are high resource intensity, high regulatory control and high failing costs (Parker, Van Alstyne, & Choudary, 2016). A prime example of an industry not easily captured in a platform is the healthcare sector, not in the last place because of the highly fragmented nature of the industry. Compared to the taxi business, a two-sided market with the driver and the passenger as the only relevant parties, the healthcare sector is characterized by many different players, such as hospitals, pharmaceutical producers, doctors, insurance companies, pharmacies, governments' regulatory instances and of course patients themselves. Other main factors complicating healthcare 'transactions' to be captured in a platform business, are the misalignment of incentives among players and the resulting coordination problems, and the often very big information asymmetries existing in modern medicine between physician and patient. As a result of these complicating industry characteristics, interactions and coordination between parties in the healthcare industry, such as the doctor patient interaction, have mostly been untouched by new business models like platforms and have not made major efficiency improvements for decades (Tandon P. , The Indian health sector and the development of 1mg, 2018).

Still, healthcare is an industry facing major global challenges and is therefore in desperate need of a revolution. The problems facing healthcare rising from the ageing world population alone, with the number of people over 60 years of age expected to double between 2015 and 2030 (United Nations, 2017), putting major strain on care productivity, necessitate radical efficiency improvements. A second major challenge facing the sector, is affordable healthcare. Healthcare costs are on the rise in both developing and developed countries, with American spending on healthcare being the highest in the world, having risen $933.5 billion USD between 1996 and 2013 (Dieleman, et al., 2017). Meanwhile, in low and middle-income countries (LMICs) where the majority of the population is uninsured, out of pocket health expenditures can have catastrophic impoverishing effects (Niëns, et al., 2010). The World Health Organization (WHO) defines catastrophic healthcare expenditure as being 40% or more than the capacity one has to pay (Kawabata, Xu, & Carrin, 2002). A 2015 study from the WHO on global ageing and adult health found that 7% of people aged 65 and higher in India faced catastrophic health expenditure (Brinda, Kowal, Attermann, & Enemark, 2015), while research from 2010 concluded that nearly 7% of the Indian population, as much as 63 million people, where forced below the poverty baseline due to healthcare expenditure (Berman, Ahuja, & Bhandari, 2010).

However, by eliminating intermediaries, easing coordination and aligning interests between the industry's parties in a patient-centred business model, platform business models have the potential to increase efficiency, bring down prices and revolutionize healthcare. Especially in developing countries, where the internet has only recently taken wings and the economy is transitioning from an offline, cash-based system towards a digital economy, lie major opportunities for platform business models to step in and improve efficiency.

Nevertheless, is the platform business model suitable to take over this very traditional market? Is the model able to decrease patient healthcare costs and increase efficiency or will regulatory restraints, powerful incumbents and the misaligned interests in the sector prove to be too big of a hurdle to overcome? In this thesis, I will try to answer these questions using a case study of a platform business start-up in India called 1mg, situated in the market as an e-pharmacy. In this case study, the focus will lie on how platforms are able to increase allocation efficiency in terms of pricing and product fit, by decreasing information asymmetries and lowering search costs through facilitating easy matching. The results of this study are that the benefits of a platform business model in the healthcare sector, cannot be realised without supporting institutions and regulations. The results of this paper can be extrapolated to platforms operating in industries with high information asymmetries and high regulatory control in countries with a similar context as India.

The remainder of this paper is organised as follows: First, the mechanics behind platforms and what makes them so successful are described in section two, before looking into the benefits to consumers of platforms and introducing the specifics of platforms in the healthcare sector. In section three, we will narrow down to the case of e-pharmacy platform 1mg operating in the Indian pharmaceutical sector, and subsequently present a research question and several hypotheses. In section four, the data and methodology of the research is described, while results are presented in section five. Section six discusses the results and elaborates on policy recommendations and future research. Finally, section seven concludes.

2. On platforms

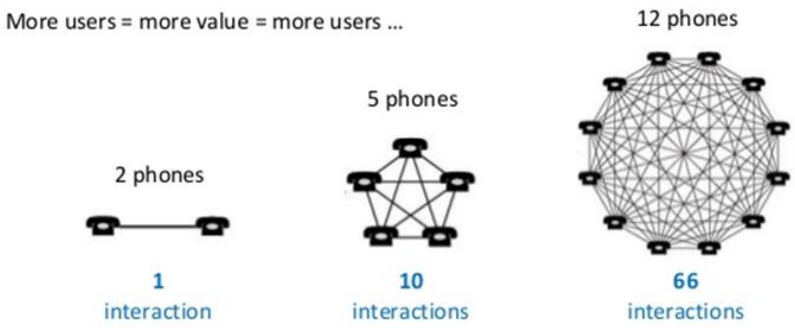
2.1 How platforms climbed to the top

A survey from 2016 by (Evans & Gawer, 2016) on the rise of platforms identified 176 platform businesses whose combined value exceeded $4.3 trillion USD. This number however is growing exponentially, and many traditionally fashioned incumbents are looking to restructure (at least a part of) their value chain towards a platform business model in order to avoid falling behind (Parker, Van Alstyne, & Choudary, 2016). 81% of executives interviewed by Accenture in 2016 reported to give the platform business model a central role in their strategy for the coming three years (Accenture, 2016). Global commerce is therefore likely to move more and more to platform based interactions in the future.

The popularity of the platforms can be contributed to several mechanics. First, a core mechanic of the platform business model is that it allows for production value to be added by parties external to the firm. Traditionally, a business model is structured linearly, meaning that value is created at the beginning of the production process and value is added every step along the way, until ultimately the finished product is delivered to the customer. This value chain is often referred to as a 'pipeline model'. Producers and customers in this model have no overlap as the entire production process is closed. In the platform business model on the other hand, a producer and a customer can be the same person. The value chain is opened up and instead of a pipeline with linear internal value addition, external producers and or users are able to add value on the forum facilitated by the platform. This allows for the aggregate production of the platform userbase to be far greater than could ever have been achieved using solely internal resources (Gawer & Cusumano, 2002). A good example is the "Appstore" by Apple, which offered the place and tools for external developers to create their own apps, which could then be downloaded by iPhone users. Along the same lines, Facebook facilitates a platform where users can share personal experiences and other content. With its users functioning as both producers and consumers of content, billions of posts have been shared on the platform without Facebook creating (barely) any content itself.

A second important mechanic of platforms, is their self-reinforcing cycle based on *network effects*, where a distinction should be made between direct and indirect network effects. *Direct network effects* refer to the mechanic in which a user's benefit from platform participation is based on the number of users with whom they can interact (McIntyre & Srinivasan, 2017). An example of a product characterised by direct network effects is the telephone: the more people have a telephone the more people you can call as the number of possible interactions increase exponentially with every new telephone owner. In figure one presented below, these direct network effects are visualised.

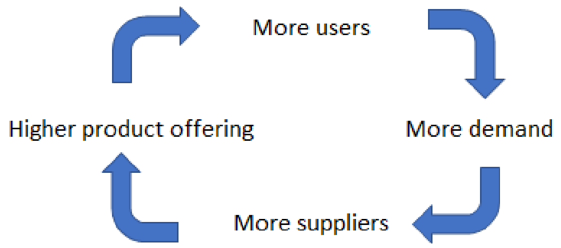
Figure 1. *Exponentially increasing direct network effects of telephones*



Source: Wikepedia.org

Indirect network effects on the other hand, occur when different sides of a market benefit from the size of the other side of the market (McIntyre & Srinivasan, 2017). In this mechanic, the more producers that join a platform, the more products are offered, the more users are attracted. These additional users in turn, attract more producers that are interested in selling to the platform's user base (Eisenmann, Parker, & Van Alstyne, 2006). A defining result of these indirect network effects is called *demand side economies of scale*. In contrast to production side economies of scale, which lower the cost of production with scale, demand economies of scale refer to the diminishing efforts needed to attract users to a platform. Moreover, once a critical mass is reached, the user base will continue to build itself through indirect network effects. This self-reinforcing cycle of indirect network effects is visually conceptualised in figure two presented below.

Figure 2. *The self-reinforcing cycle of network effects*



Indirect network effects can give companies a monopoly comparable to the monopolies resulting from supply side economies of scale; once a certain platform enjoys a large enough user base, competitors of that platform will have a hard time persuading both producers and customers to switch to a platform with less producers to choose from and customers to sell to (Shapiro, Carl, & Varian, 1998). Other examples of industries with demand side economics of scale besides the smartphone application market are freelancing websites such as Upwork, transportation apps such as Uber or Blabla Car, or the gaming industry with platforms from Sony's Playstation and Microsoft's Xbox who compete in attracting the largest userbase and the most game-developers for (exclusive) games (Venkatraman & Lee, 2004).

A third major mechanic in the success of platforms is scalability. The first driver of the scalability of platforms derives from positive network effects, which has been discussed above. The second driver of scalability is technological. Once a firm has built a digital platform, joining a platform for users and producers is often as easy as downloading an app or creating a profile while the firm incurs negligible marginal costs for adding these users or producers to their userbase inventory. The same goes for additional transactions, once the requisite technological infrastructure is deployed (e.g., software and servers), a marketplace platform can serve additional transactions at trivial marginal costs (Li, Pisano, & Zhu, 2018). Additionally, because platform interactions take place online, a platform firm's target group is not location specific. These factors combined allow platforms to easily penetrate foreign markets and grow exponentially. A prime example is housing provider Airbnb, who only 10 years after being founded in 2008, is operating in 81,000 cities in 191 countries, providing housing experiences to over 5 million users (Airbnb, 2018).

Besides these major mechanics, there are some other innovative strategies platform businesses use to run a successful business. A first example is the de-linking assets from value. By independently trading and making the best use of an asset, without looking at asset ownership, asset utilization can be greatly increased and thereby efficiency improved (Parker, Van Alstyne, & Choudary, 2016). Well known examples are Uber, offering the world's largest taxi network without owning any vehicles, and again Airbnb, who does not own any of the rooms being rented on its platform. The assets however, in this case the cars of the Uber drivers and the houses of the Airbnb renters, already existed. The platform only offers the possibility to increase these assets' utilization while offering their owners a way to monetize on this extra utilization.

Another important strategy many platforms employ, is a user review system which is able to decrease information asymmetries regarding products or services, as well as filling in for the gap in consumer trust between traditional offline transactions and buying products or services from strangers on the internet. Decreasing information asymmetries and quality uncertainty plays in the favour of buyers, as described in Akerlof's seminal paper on the car industry and the market for lemons (Akerlof, 1978). In this paper, Akerlof defines information asymmetries as the problem of (car) sellers having more information about the product (cars) they are selling than buyers could hope to have. Usually this information asymmetry concerns the quality of the product and is thus relevant in whether the product is fairly and competitively priced. The existence of information asymmetries therefore decrease the chances for the buyer to have a good value for price purchase. Platforms diminish information asymmetries by aggregating all products and their prices in one place, providing information about these products and by employing a user review system in which products or services are rated by their buyers.

Besides decreasing information asymmetries regarding the products, the review system is also used to increase trust by allowing users to rate users of the other side of the platform; buyers (and or producers) give the producer from whom they bought their product or service a rating for the transaction. As the information regarding a product on a platform is usually given by its seller, this user review mechanic allows to filter out sellers providing wrong information or bad service. For example, when a seller on Ebay sells fake products, or an Airbnb renter advertises his property with photos that do not match the actual accomodation, these producers will soon lose customers because of the bad ratings they receive as sellers. Likewise, if a Uber user is given bad ratings by his or her drivers, finding a driver willing to pick him up instead of users with a higher rating will be harder. Platforms also withhold the right to deny access to its platform to users and producers, whenever they receive reviews that justify a ban. With this system of users and producers rating each other, platforms are able to keep their marketplace clean of unreliable users and give customers a feeling of trust, without having to put any effort in quality control themselves. Similarly, with product reviews by users, information asymmetries are lowered and the information available on the platform increases in value, again increasing trust, all without the platform having to write any reviews themselves[1]. Again, this mechanic scales really well, making building consumer trust in new markets easy, which effectively lowers entry barriers in foreign markets. Some platforms have even made decreasing information asymmetries and providing trust their core business with great success. The popularity of platforms such as Yelp or TripAdvisor providing information and user reviews, has made (tourist) consumer-dependent entrepreneurs such as restaurant-, activity- or hotel-owners in every major city nowadays put very big value on their ratings, as good ratings will attract customers, while bad ratings will repel them.

2.2 Benefits of platform business models

The recent emergence and near immediate dominance of platform businesses in many industries has changed the global economy in some major ways. First of all, thanks to the aggregation on platforms of both producers and users all in one place, allowing for easy matching, search costs have been lowered and allocational efficiency is increased, while at the same time prices are driven down because of increased competition. Search costs are defined as “the cost incurred by the buyer to locate an appropriate seller and purchase a product” (Stiglitz, 1989). These costs used to be the result of physically visiting multiple stores to search for the product you want to buy at the best available price. However, with the arrival of the internet, information about prices and product characteristics has been made available online by platform businesses, allowing for (nearly) effortless

[1] Platforms often incentivize users to write reviews by offering discounts or chances to win prices.

and costless product comparison and moving the market closer to the classical ideal of a Walrasian Auction, with costlessly fully informed buyers (Bakos, 1997).

Because of the increase in information available to buyers and the lack of importance of a seller's geographic location due to product home delivery, the market power of sellers is decreased, taking away their ability to leverage information asymmetries or locational benefits to extract monopolistic rents. Following the decrease in search costs, competition in the online market places (platforms) increases, driving down prices and moving the market closer to a competitive pricing equilibrium. Additionally, buyers enjoy improved allocational efficiencies since they have a better chance of finding their preferred product for the best price. These allocational efficiencies in combination with lowered search costs improve the net social surplus (Bakos, 1997). A good example of a platform lowering search costs by aggregating both sides of the market is redBus, an Indian start-up founded in 2006 which consolidated the many different bus operators and schedules of the highly fragmented bus system of India on a national scale, allowing customers to easily compare and purchase inter- as well as intra-state bus tickets (redBus, 2019).

There is also benefit to lower search costs for sellers as well. Despite the increased competition lowering sellers' prices, aggregation of platforms benefits the sellers by providing visibility of their offerings and facilitating interaction with their target group. Because search costs for sellers trying to find buyers are also decreased by platform aggregation, and because joining a platform as a seller is relatively easy compared to finding your own buyers by using for example traditional marketing, entry barriers in a market aggregated by a platform are lowered. The resulting rise in market entrants, increases product variety as well as competition, lowering prices even more and making the market conform more and more to perfect competition. Then again, the resulting increase in competition can also deter sellers to join a platform, especially in sectors characterized by a lack of diversification opportunities such as the steel industry (Rysman, 2009; Ellison & Ellison, 2009).

A second general advantage to platforms, is that platforms allow for a more efficient value chain by dis-intermediating (eliminating intermediaries) industries. Especially markets with high product diversity, high search costs and a high number of intermediaries, are vulnerable to disintermediation. A prime example is the eTourism market, where big platforms have driven out traditional travel agents, as predicted by (Buhalis & Licata, 2002), by making use of their scale and aggregation of both sides of the market and offering entire holidays. Holiday packages today can include every aspect of a holiday: pickup at home, the flight, a rental car, over-night stays and activities, while all of these aspects used to be sold by different traditional intermediaries. However, even though the scale of platforms allows them to eliminate intermediaries and increase efficiency, it is questionable whether this will be bring down prices as well. Due to the scale of a platform increasing network effects, as discussed above, it could be the case that a winner-takes-all dynamic will develop, leaving the dominant platform in a monopolistic position with the opportunity to increase transaction margins in its platform. For the sake of competition and low prices therefore, it is important that platforms face competition as well, as argued in (Jullien, 2005).

A third benefit of platforms, is that they are drivers of innovation. A total of 11,585 patents in 2014 were filed by just nine platform businesses from the US (Evans & Gawer, 2016). The drive to innovate of these companies seems to be driven by the desire of developing technologies which will form the foundation on which competitors and complementors built their products, essentially making this company the ‘platform leader’ resulting in a competitive advantage (Gawer & Cusumano, 2002). A second explanation of the high levels of innovation among platform businesses is the innovation ecosystem. As discussed above, opening up a platform to external developers and producers who can use the platform technology facilitates higher aggregate production and therefore higher innovation, than would have been possible with only the platform business’ internal resources (Gawer & Cusumano, 2002).

Lastly, the de-linking of assets from value by platforms, as discussed earlier, has greatly increased global asset utilization. One could argue that the popularity of sharing-based platforms such as Uber and Airbnb, has slowed down production of taxi-vehicles or the building of hotels. At the same time, private owners who rent these assets on platforms have been able to monetize this extra utilization. Therefore, assets have less downtime, prices of usage of these “shared” assets are lower than traditional asset rent, and the owners of those assets have increased their income without needing to make new purchases. Sharing platforms have therefore, arguably, increased average purchasing power. Additionally, one could argue that these kind of platforms are improving global sustainability by lowering the average environmental impact per asset or service. An example of a sharing platform with evident sustainability benefits is carpooling app BlaBlaCar, a platform where people who own a car can list a ride they are planning to take and where people wanting to travel the same route can pay the owner of the car to be a passenger, instead of driving another car the same route as well.

2.3 Platforms and the healthcare sector

As seen in the introduction, healthcare is the industry most in need of a revolution and efficiency improvements, because of the major challenges facing the sector on a global scale such as the ageing population and healthcare affordability. Then how come, that when platforms everywhere are able to leverage mechanics that allow them to revolutionize markets and disrupt incumbents, and when platform businesses have major benefits to consumers, the healthcare industry has yet to be revolutionized by platforms?

The reasons why some industries have been thoroughly disrupted by platforms already, such as media and telecom, while other sectors such as banking, education and healthcare are yet to be transformed, depend on several industry characteristics. There are four industry characteristics which increase platform disruption susceptibility: First, high information intensity allowing for high levels of digitization of that information. Second, the presence of non-scalable (human) gatekeepers, such as editors in the publishing industry[2], allowing for dis-intermediation by a platform. Third, a high rate of industry fragmentation giving use to market aggregation and fourth, the presence of (extreme) information asymmetries allowing platforms to reduce search costs and level the playing field by decreasing these asymmetries. On the other hand, three industry characteristics that decrease platform disruption susceptibility, are high resource intensity, high regulatory control and high failing costs[3] (Parker, Van Alstyne, & Choudary, 2016).

Healthcare is an industry characterized by all industry characteristics relating to susceptibility of disruption, both negative as well as positive. This gives the sector huge but difficult to realise potential. Additionally, besides the foremost complicating factor of high regulatory control, healthcare is characterized by another factor making the industry more difficult to capture by platforms, namely, the interconnectedness of players in the market paired with the misalignment of interests of said players. While theoretically all players in the market should work towards the same goal of high quality patient care, the reality is often different. With health insurers, pharmaceutical producers, pharmacies and even hospitals and doctors all playing the game of profitability and market shares within their own respective playing field, extracting value in every step of the 'healthcare value chain', healthcare quality and especially affordability often pay the price (McKone-Sweet, Hamilton, & Willis, 2005; Kaplan & Babad, 2011). Because of these misalignments of interests, there have long been calls for better coordination between players to improve health outcomes and efficiency in achieving those good health outcomes, especially calls for digital coordination (Cebul, Rebitzer, Taylor, & Votruba, 2008; Hill & Powell, 2009).

In spite of these complicating factors in the healthcare sector, there have been several successfully launched healthcare platforms. An example is Cohealo, a sharing based platform founded in 2012 in the US, which facilitates a platform where health providers can rent or hire professional

[2] Nowadays, writers can publish their work on online platforms, where the community of users rates this work and traditional editors who judge the work of writers are made redundant.
[3] Failing costs in this case refer to the potential costs of a mismatch by the platform; in healthcare, matching a patient to the wrong doctor has bigger costs than OKCupid suggesting a less fitting partner.

equipment during downtime, thereby raising utilization rate, lowering costs and granting access to specialized, expensive equipment such as MRI-scanners, which otherwise would have been unavailable to small scale operators (Cohealo, 2019). Cohealo is however, one of the few healthcare platforms operating between the players in the healthcare industry with a business to business model. Most of the healthcare platforms focus on the business to consumer model, facilitating some kind of patient interaction. Doctor.com, MDLive, 1DocWay and America Well are some examples, all providing matching between doctors and patients and online or offline interaction with these doctors. Another example of a healthcare platform with a patient focus is the popular format of online pharmacies, more generally referred to as e-pharmacies. Healthwarehouse.com is again an American example operating as an e-pharmacy, where users can order over-the-counter (OTC) medicines and prescription medication (RX) to be home-delivered.

However, the biggest need and opportunities for platforms to revolutionise healthcare, are in low and middle income countries (LMICs). It is no secret that most developing countries suffer from bad healthcare quality, as most recently reported in a systematic review of countries by healthcare quality from a global research effort funded by the Bill & Melinda Gates Foundation (Fullman, et al., 2016), while those same countries also face the largest population growth rates, putting further strain on their healthcare systems.

Nonetheless, these countries also provide some of the greatest opportunities for platform businesses in healthcare because of three major reasons. First, there has been rapid adoptation of e-commerce in developing countries, effectively lowering entry barriers regarding consumer trust. At first, developing countries were slow to catch up with the rapid development of e-commerce in developed countries due to, among other factors, lacking infrastructure in terms of internet coverage and mobile financial services (MFS). However, the last few years many developing countries have made major steps in these areas, with increases in network coverage and stability, as well as sharply falling costs of mobile network coverage and newly developed MFS. By illustration, MFS platforms like PayTM, founded in 2010 in India, facilitate e-wallets which customers can use to pay online for their products with nearly every e-commerce website. These improvements, in combination with further penetration of the internet, falling costs of smartphones and increasing urbanization, has led to an online kind of lifestyle. Today, everything can be ordered online and home delivered with hugely popular apps such as Go-Jek (Indonesia) or Big-Basket (India), providing transportation on the back of a scooter, home delivery of groceries bought by the delivery personnel at brick and mortar stores, bigger shopping items from hardware stores and even services such as at home massage sessions (Go-Jek, 2019). The popularity of online commerce has made people comfortable with ordering online, and has thereby effectively lowered the entry barrier of consumer trust for e-commerce.

A second reasons for the huge opportunities to platforms is the fact that many of these countries are still in the early stages of making the transition from an offline-, cash based economy towards a digital economy. This means that there are many opportunities for e-commerce platforms to step into markets where no other company has taken a leading role yet, and leverage the possibilities resulting from digitization, as well as leveraging the knowledge which can be extracted from the data created by this digitization.

Lastly, developing countries are often characterized by institutional voids, both in terms of social as formal institutions. Institutional voids, which can be defined as 'situations where institutional arrangements that support markets are absent, weak, or fail to accomplish the role expected of them' (Mair & Marti, 2009), create opportunities for 'institutional entrepreneurs', first described by Dimaggio as 'organized actors with sufficient resources who see the opportunity to realize some form of interest in new institutions' (Dimaggio, 1988). Especially the new possibilities deriving from the internet and the following emergence of online commerce, created (formal) institutional voids regarding for example regulations on licenses for e-commerce players selling regulated products. By effectively engaging in institutional entrepreneurship, there is a lot of direction to be given to the newly found industry and therefore these institutional entrepreneurs have the possibility of setting the rules of the game in their advantage.

A country that fits every criteria regarding platform disruption susceptibility in healthcare mentioned above, is India. As a developing country with world's second biggest population, a low-quality, unaffordable and fragmented healthcare system, increasing rates of urbanization and high internet adaptation, the sector holds both major challenges as well as major opportunities for platform businesses to revolutionise the industry. Luckily, these opportunities have not gone unnoticed, and several platforms have taken up the challenge of revolutionizing the market. Because of the potential for healthcare efficiency improvements and the presence of healthcare related platform business start-ups, India is the perfect setting to investigate the potential of platforms in healthcare. The remainder of this paper will therefore focus on the case of a platform in India called "1mg", operating as an e-pharmacy.

3. On the Indian pharmaceutical sector and 1mg

3.1 The Indian pharmaceutical sector

Before we look into the case of 1mg, some context on the market the platform operates in, the Indian pharmaceutical sector, is needed.

In 2017, the Indian pharmaceutical sector was valued at $33 billion USD. The industry is world's biggest provider of generic drugs, accounting for 20% of global exports in terms of volume, and supplies over 50% of global demand for various vaccines. Nationally, the sector's turnover reached $18.12 billion USD and grew 9.4 percent compared to 2017 (Indian Brand Equity Foundation (IBEF), 2019). Despite these impressive figures however, the growth and success of the sector does not seem to benefit the Indian population. The costs of drugs is considered one of the main reasons for high poverty rates, as 72% of out-of-pocket expenditures (OOP) are drug related (Garg & Karan, 2008), and as much as 63 million people are pushed below the poverty baseline due to healthcare expenditures according to research by (Berman, Ahuja, & Bhandari, 2010). These catastrophic healthcare costs, as described in the introduction, especially impact the population living in rural areas (Van Doorslaer, et al., 2007). To make matters worse, the number of households facing catastrophic healthcare expenditures is growing, according to a 2014 national health policy draft report from the Government of India; "incidence of catastrophic expenditure due to health care costs is growing and is now being estimated to be one of the major contributors to poverty. The drain on family incomes due to health care costs can neutralize the gains of income increases and every Government scheme aimed to reduce poverty." (Ministry of Health and Family Welfare, 2014). Meanwhile, public spending on healthcare does not seem to be the governments priority, as Indian domestic general government health expenditure accounted for only 1% of gross domestic product (GDP) in 2015 (World Health Organization, 2017), ranking 187th out of 194 countries represented in the statistics. (Kempen, 2017)

An important reason for why high prices of healthcare weigh this heavy on the population, is because of the lack of health insurance penetration and availability. According to a 2018 report by EY on the health insurance sector of India, only 20% of the population has health insurance coverage (Ernst & Young, 2019). Health insurance penetration is hold back by several factors, among others the frugality of the Indian population, who consider spending money on premiums they ultimately do not use as wasteful, as well as the operational difficulty to insurers of consolidating and reviewing claims from cash-based healthcare transactions on fraud and other checks.

However, the reasons for the high healthcare costs seem mostly due to institutional voids in the regulatory system, unfortunately formulated regulations and a lack of control, resulting in strategic responses of players misusing these flaws to their advantage. Regulations in the Indian pharmaceutical industry often are too broadly or too narrowly specified, which gives the players in the market the opportunity to behave strategically and circle around the regulations' intent. Furthermore, there is insufficient control on compliancy and too few punitive consequences on ignoring or abusing regulations, which decreases the credibility of the government and its regulations and thereby increases the number of transgressions. As argued by (Oliver, 1991), active defiance and manipulation of institutional rules and requirements are most likely to occur when the degree of legal coercion is low.

Transgressions occur in multiple layers of the pharmaceutical value chain. At the top of the chain, pharmaceutical producers engage in strategic firm behaviour in order to avoid government regulations aimed at decreasing the costs of essential medicine. In 2013, a selection of medicines which are frequently used and crucial to basic health in India, has been composed in the National List of Essential Medicines (NLEM). Based on this list, the government developed regulations starting mid 2013 that imposed price ceilings on some, but not all formulations of these medicines. However, this regulation missed its mark on several points. First of all, the ceiling prices were based on the average price to consumers in the months leading up to the start of regulation, instead of a cost-based price ceiling, which made pharmaceutical producers collude to increase their prices in the months leading up to the start of the regulation, in order to set the ceiling prices as high as possible (Bhaskarabhatla, Anurag, Chatterjee, & Pennings). Additionally, the partial regulation of formulations, on for example the 500mg Paracetamol formulation, but not the 1000mg strength formulation, opened the door for effort diversion of the pharmaceutical producers into unregulated formulations. The producers focussed their attention on unregulated formulations without a price ceiling and therefore with bigger margins, by lowering the production of regulated formulations. This created a supply shortage which allowed them to sell more of the relatively higher priced, unregulated formulations of the same drug (Bhaskarabhatla, Anurag, Chatterjee, & Pennings). Lastly, besides the lack of improvement in affordability, there could also be negative health consequences of the poorly formulated regulation for patients. These potential negative health consequences result from pharmaceutical producers pushing unregulated formulations over the ones included in the price control, which are arguably the most fitting formulations in general cases (Soma, 2013; Morgan, Griffiths, & Majeed, 2005). Since the intended results of the regulation are avoided, it is doubtful whether the regulations have improved the situation at all, adding to the sceptical school of thought who question whether the benefits of regulations outweigh the effort and costs of designing, implementing and enforcing them (Peltzman, 1975) (Kempen, 2017).

Further down the pharmaceutical value chain, brick-and-mortar pharmacies are also able to mitigate the government's efforts of lowering medicine prices due to a lack of control. By colluding in a cartel under the All India Organisation of Chemist and Druggists (AIOCD), over 750,000 pharmacies throughout the country enforce a 30% trade margin (10% for wholesalers and 20% for retail channels) without adding any value to the table besides stocking medicines. The cartel enforces these margins through asymmetric punishment strategies, whereby they use sale and supply embargoes to punish both pharmaceutical suppliers as well as pharmacies respectively, when either opposes the cartel or refuses to cooperate by acting in the cartel's interest, as shown in (Bhaskarabhatla, C., & Karreman, Hit Where It Hurts: Cartel Policing Using Targeted Sales and Supply Embargoes, 2016).

Another problematic section of regulation is the way drugs are prescribed to patients. First off, it is important to consider the nature of the product that is medicines. Unlike other commodities, medicines by default have very little product differentiation. This is because a medicine works because of the active pharmaceutical ingredient(s) (API) which it contains. Once, after extensive research and development (R&D), a new (combination of) API is determined to be efficient in battling the disease or symptoms targeted, a patent is granted to the developing company for a number of years, which gives the company the possibility to earn back its investments incurred in R&D. After this time the patent is revoked, which opens up the possibility for other pharmaceutical producers to fabricate generic versions of the same medicine. Since they do not have to invest in research and development, generics are usually substantially cheaper than the original branded medicine. Additionally, as the API in a medicine is a unique molecule, there ought to be no difference between the same medicine produced by multiple companies, besides possibly the level of purity of the medicine and the excipients[4] included. However, when proper control on the production of these generics is enforced trough audits and checks, a generic medicine should be in no way lesser in quality compared to the original branded medicine.

Internationally, generics are sold under agreed upon short names, called International Non-Proprietary Names, also referred to as a "salt", an example being Paracetamol. As mentioned in the beginning of this chapter, India is global leader in the production and export of these generic medicine thanks to the medicines' high quality and low costs, thereby providing cheap medication worldwide. Nationally speaking however, the story is unfortunately quite different, since the distinction between branded and generic medicines in India is clouded by the pharmaceutical producers' selling 'branded generics'. By selling their generic medicines under a brand, pharmaceutical producers have been able to create brand recognition for their generic medicines over time by leveraging their reputation as

[4] Excipients are for example fillers, binders and other ingredients in a formulation besides the API, to help the drug to be delivered to the body as efficient as possible.

trustworthy producers. Thereby, pharmaceutical producers have effectively created product differentiation out of thin air, giving themselves the leverage to price higher than their competitors who produce the exact same product.

At the same time, doctors in India are not required to prescribe medicine to a patient using the salt name, but specifically prescribe brands of their choosing from the concerning salt. As pharmaceutical producers in India are not allowed to market specific brands of medication at the patient level, a lot of investment is made to market their medicines to doctors directly (Aditya & Sindhwani, 2014). Under the pretence of 'educating' doctors, manufacturers spend huge amounts on gifts, paid holidays, jaunts and other junkets to get doctors to prescribe their brand of an out-of-patent medicine. Through these efforts, manufacturers succeed in making doctors prescribe expensive branded generics instead of cheaper alternatives (Aditya & Sindhwani, 2014). Even worse, because the doctor prescribes a brand instead of a salt, the patient is left in the dark of potential cheaper alternative brands and generics and pays unnecessarily high prices at the pharmacist, who in turn also benefits from this mechanic as selling higher priced medication means his 30% margin returns higher absolute income.

The negative impact of these problematic dynamics in the pharmaceutical market is further enhanced by the relatively undeveloped and uneducated population of India. In 2018, India ranked 104th out of 149 countries in education on the Legatum Prosperity Index (Legatum Institute, 2018). As a result of the low quality educational system, India still faces low literacy rates of just 74%, well below the world average of 84% (Cencus India, 2011). Because of these reasons, the educational gap between physicians and the average poor and uneducated patient are huge. Additionally, in contrast to Western societies where doctors have to deal with patients who tell them what to do after self-diagnosing with information found online, in Indian cultures doctors are still seen as highly respectable and knowledgeable members of society, with whom you as a patient, do not argue. Ultimately, information asymmetries regarding the nature and pricing of generic medicines are therefore only increased by pharmaceutical producers branding out-of-patent medicines, doctors prescribing those brands instead of salts, and an uneducated population who does not ask questions.

3.2 The case of 1mg

As is the case in America, most platforms operating in the healthcare sector in India are patient focussed. Care24 for example, is a platform founded in Mumbai in 2014, which facilitates matching between caregivers and patients not admitted at hospitals (anymore) but needing support at home, as well as infant or elderly care (Care24, 2016). Other examples are Practo, Netmeds and Pharmeasy, all applying the same platform strategy of connecting two sides of the pharmacy market; patients and pharmacies. The platforms match the demand for medicines with the supply of pharmacies in the vicinity of the order address, and are consequently able to home-deliver RX and OTC medication of these pharmacies at discounts, by making use of their scale through aggregation and dis-intermediation of the market. Additional service offerings by the companies include e-consults with doctors, facilitating diagnostic tests with at home sample collection and the sale of medical devices and other health or wellness related products.

Platform 1mg.com (1mg) offers all of these same service offerings, as well as pill reminder and online health information storage functionalities in the 1mg app. The company, originally called HealthKartPlus, was founded by Prashant Tandon, Gaurav Agarwal and Vikas Chauhan in 2012. They started the e-commerce healthcare platform, by operating the generic drug-search business of Healthkart, an online store for health products. After separating from Healthkart and rebranding as 1mg, acquiring Homeobuy.com in 2015 to enter the homeopathy market and acquiring Medd.in in 2016 to add the radiology segment, 1mg.com now positions itself as the one health app for all consumers in India (1mg, 2017; Kempen, 2017). Since the start of the company, 1mg has received over $80 million USD funding from blue chips investors such as Sequoia and HBM Healthcare Investments and won several domestic as well as international awards, such as the award for best made app in the Indian healthcare category at the Global Mobile App Summit & Awards (GMASA) 2016 (Crunchbase, 2019; 1mg.com, 2018).

However, there is an essential difference between 1mg and its competitors mentioned above, which makes 1mg the most interesting case to study, namely; having information provision as its core competence. In contrast to its competitors, 1mg has an extensive database on its platform, with information on every drug (salt) as well as on all brands and formulations that are available of this drug. The platform provides information on medication usage, the disease the medicine works against, potential side effects, brands and formulations available and, specific to each brand or formulation, provides additional information on how to use the drug. Additionally, 1mg provides pictures of the packaging, medicine related warnings, information on dangerous interactions with other drugs, alternative brands of the same drug available and possible savings from substituting, as well as user questions answered by 1mg doctors and user reviews of the drug considering for example experienced side effects. 1mg has a team of over 50 doctors who have built this extensive database and are working daily to complement it and to keep the information up to date. The team additionally writes articles on relevant health issues facing the Indian population in an effort to educate them on health risks, as well as to improve medicine adherence and finally, health outcomes. Even more so, the team is actively working to improve healthcare on a national level by contributing to research. For example, they are actively engaging in institutional entrepreneurship as they have written a paper with policy recommendations on how to improve the currently problematic medicine classification system regarding habit forming drugs and other factors (Tandon, et al., 2017).

The information provided by the platform is so extensive and detailed, that it is the main reason for people to visit the platform. When looking at application analytics from AppAnnie[5], we can see that in the healthcare category of applications, 1.7% of devices with at least one app from the category installed, has installed the 1mg app. More importantly, 38% of the time spent by these device owners in applications from the healthcare section, is spend on the 1mg app. In contrast, these rates for the second best performer and competitor of 1mg, Practo, are 0.9% and 9% (1mg.com, 2018). Additionally, only 1% of visits on 1mg.com actually result in the purchase of a product or service. These figures combined, tell us that the 1mg platform is mainly visited because of its extensive and high quality information[6]. Lastly, making use of the platform business model reviewing mechanic, 1mg's users are complementing to the database by writing user reviews on the efficacy, side effects and price level of the medicines sold on the platform.

As 1mg is a platform business, the company is able to leverage the mechanics discussed in chapter two and should theoretically be able to decrease medicine prices, by dis-intermediating the market and increasing competition, as well as lowering search costs to consumers. However, as 1mg's core competence is providing information, we will look solely into the effect of 1mg decreasing information asymmetries. More specifically, we will focus on 1mg's provision of price comparison between brands and formulations of the same salt, since affordability of healthcare is one of India's biggest challenges.

Since 1mg facilitates easy price comparison, the company essentially decreases search costs, which should normally lead to optimized allocational efficiency regarding price and product fit, as discussed in the theoretical framework. However, due to the nature of healthcare and the problematic regulations discussed earlier concerning doctors prescribing brand, this might not be the case. Even though 1mg can show different brands and prices of identical drugs regarding API, strength and formulation of the medicine, the company is by law prohibited to sell any other brand within said salt formulation to patients, except for the brand prescribed to the patient by his or her physician. Therefore, patients do not have the power to select and buy the medicine brands they want themselves. When a patient wishes to substitute the brand prescribed by his doctor to a cheaper brand after using the price information found on 1mg.com, he needs to get back to his doctor and ask him to

[5] AppAnnie is a platform which analyses usage of mobile applications and sells this information as a product to interested company representatives.
[6] Even doctors appear to be using 1mg as a reliable online information source.

prescribe the brand he desires. This however, means high transaction costs[7] for the patient as he needs to get back to his doctor and convince him to write a cheaper prescription. The doctor might not be willing to do so however, since pharmaceutical producers incentivise doctors to prescribe certain brands. Therefore, it is questionable whether the diminishing of information asymmetries regarding prices realised by 1mg, does result in a customer getting a prescription for and being able to buy a cheaper brand.

Nonetheless, based on the above, the following research question is formulated:

Does the decrease of the information asymmetry regarding prices of alternative brands within a salt and formulation realised by 1mg's price comparison tool, lead to patients substituting towards cheaper brands?

3.3 Formulation of hypotheses

Following the literature on information asymmetries and the specifics presented on the Indian pharmaceutical sector and 1mg, the ensuing hypotheses are formulated:

Hypothesis 1: The higher the number of times a patient orders a certain formulation of a salt on 1mg, the lower the dosage price will be.

When a patient orders a medicine on 1mg, he is presented with information on cheaper alternative brands of the formulation of the salt prescribed by his physician (when cheaper alternatives are available). By seeing this information, the patient is incentivized to substitute towards a cheaper alternative brand and ask his doctor for a new prescription of this brand next time he needs the medicine. The more orders of a specific formulation a customer makes on 1mg.com, the more often the patient is exposed to the information on cheaper alternatives, and therefore the likelihood of him substituting increases. As after substituting to a cheaper alternative brand the price per dosage of medicine is lowered, we expect the dosage price to decrease as the number of orders increase.

Hypothesis 2: The higher the number of alternative brands available within a salt, the lower the dosage price will be.

As economic theory suggest, the higher the number of sellers of a product, the bigger the price dispersion. When there is only one seller of a specific medicine (formulation), the patient has no possibility of substituting. When there are many however, the patient has many alternatives and corresponding prices to choose from. The price comparison tool by 1mg in that case therefore provides the most information and the biggest potential decrease of the information asymmetry. As a result,

[7] Transaction costs are defined as the costs in terms of time and effort, involved in buying a certain good.

the higher the number of alternatives available, the more plenty are the opportunities for substituting towards cheaper brands and therefore the lower the dosage price should be.

Hypothesis 3: Patients with a chronic disease are more likely to substitute to cheaper brands.

When a patient faces an acute health issue, there is a time element involved in buying medicine. The patient will want to recover as soon as possible and therefore receive medication as soon as possible. It is therefore unlikely that in the case of acute health issues, a patient will take the time to return to his physician and ask for a cheaper prescription, as that could take days. Rather, the patient is likely to take his prescription to a brick-and-mortar pharmacy to get his medication immediately. Additionally, medication for acute health problems is usually able to fix the issue with a one-time purchase, like a strip of medicine directed at fighting a fever. Patients suffering from chronic diseases such as diabetes or health issues with a long term recovery on the other hand, have higher incentives to exert the effort to try and substitute to a cheaper brand, as they can achieve long term cost savings which outweigh the transaction costs of requesting a new prescription from their doctor. Additionally, patients suffering from chronic diseases will keep ordering the same formulation of a drug for the duration of the disease or until his physician sees the need to change the formulation, and as a result the patient orders medication on a frequent basis and is presented with the information on cheaper alternatives more than patients ordering medicine for acute health issues. Therefore, we expect patients ordering medicines for chronic conditions to have a higher likelihood of substituting than patients ordering medicine for non-chronic diseases.

Hypothesis 4a: During the years of operation of 1mg, the number of substituting orders out of total monthly orders increases.

As 1mg growths and matures, the amount and quality of (the delivery of) information it provides to customers is improved. At the same time, more and more patients should realise the possibility of substituting towards cheaper alternatives. The awareness of this possibility among the customers of 1mg is in turn expected to increase, especially when considering mechanisms such as word-of-mouth (WOM), where customers tell friends and relatives about the information provided on 1mg and the possibility of substitution, and considering the poor and frugal nature of the Indian population. Using this logic of increasing substitution- awareness as 1mg matures, the following additional hypotheses are formulated:

Hypothesis 4b: During the years of operation of 1mg, the monthly percentage of users who substitute increases.

Hypothesis 4c: During the years of operation of 1mg, the average number of orders before substituting decreases.

Hypothesis 4d: During the years of operation of 1mg, the percentage of money saving substitutions out of total substitutions will increase.

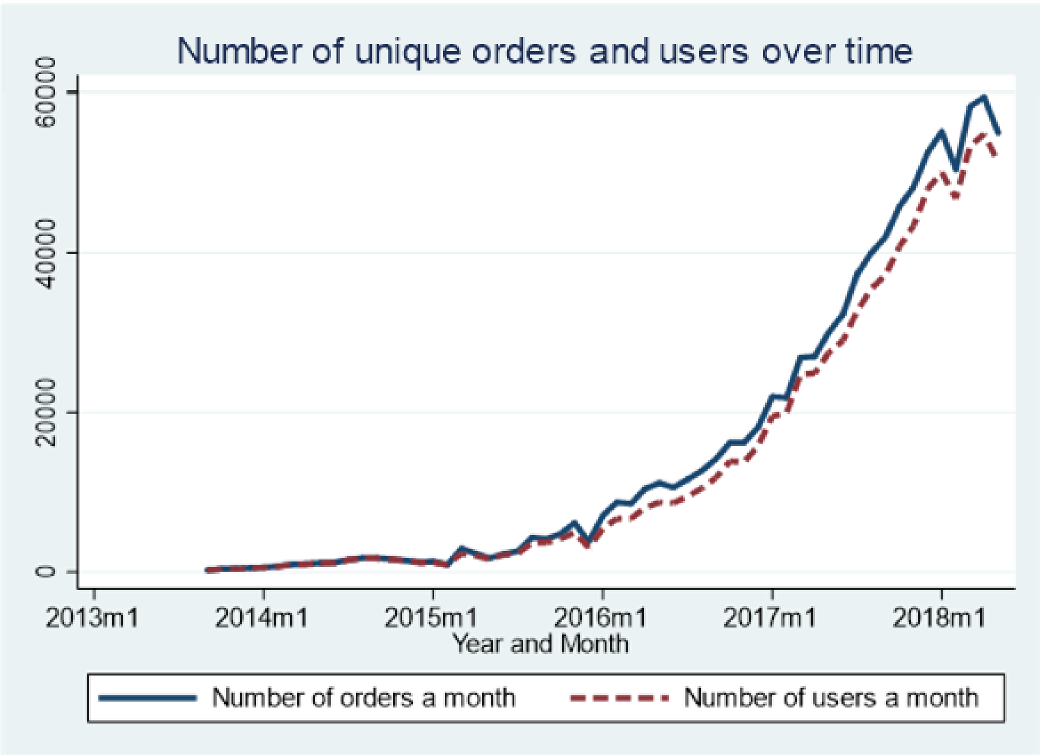
In this last hypothesis, a distinction is made between money saving substitutions and all substitutions, in which a money saving substitution refers to a user substituting towards a cheaper alternative. In this case, the assumption is made that the user substitutes because of economic (money-saving) reasons. When a user substitutes towards a more expansive or equally priced alternative on the other hand, we assume the substitution is made because of efficacy or preferential reasons, such as the user not liking the size or taste of tablets, or the user’s doctor prescribing a more expansive brand he believes to be more effective. With the same logic as hypotheses 4a trough 4c, we expect the number of money saving substitutions as a share of total substitutions, to increase over time.

4. Data and Methodology

4.1 The 1mg order data

In this thesis, order data of 1mg spanning a time period of 6 years, starting from the 3rd of September 2013 up until the 31st of May 2018, is used for analysis. During this time, 1mg has delivered nearly 1.5 million orders, which consisted of 3,2 million drugs[8] of 2,347 unique salts containing 14,319 brands to 370,717 unique users. Looking at the number of orders a month plotted over the period of the data, we can see a clear growth of orders touching 60,000 orders during the last months of the data. Similarly, we can see a strong growth in the number of unique users a month, averaging over 50,000 users a month at the end of the dataset. Both metrics are plotted in the figure three below.

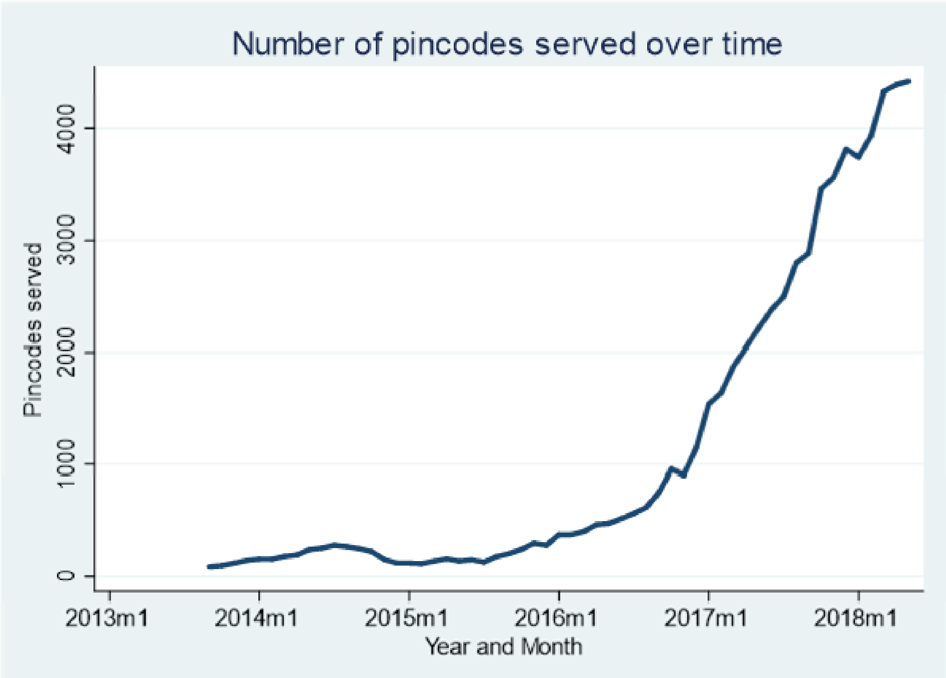
Figure 3: *Unique orders and users of 1mg over time*



If we look at the geographical reach of 1mg, by studying the number of unique pincodes[9] 1mg has delivered orders to, we can see similar growth as displayed in figure four below. Especially in the last two years of the dataset, the geographical reach of 1mg has increased significantly, growing eight times over from an average of 500 unique pincodes at the start of 2016 up to 4000 pincodes served at the beginning of 2018.

[8] Each order can contain multiple drugs.
[9] Pincodes are area codes used in India similar to postal codes.

Figure 4: *Geographical reach of 1mg expressed in the number of pincodes served*



When we compose the number of delivered orders on a district level instead of a pincode level, we can create a choropleth map of the number of delivered orders in districts to visualize the growth of the geographical spread of 1mg. In the figures below, the number of orders per district in the first month of 2016, 2017 and 2018, are mapped. We can see the geographical reach of 1mg visually increasing from just a few districts to the bigger share of districts in India:

Figure 5 & 6: *Choropleth mapping of the number of orders by district in January 2016 and 2017*

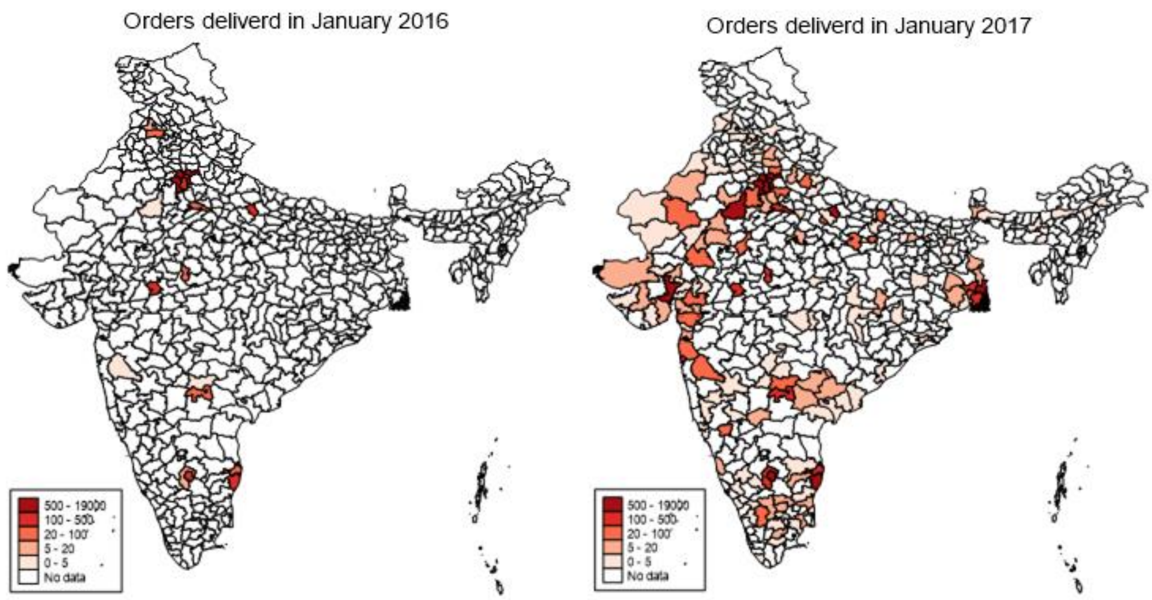
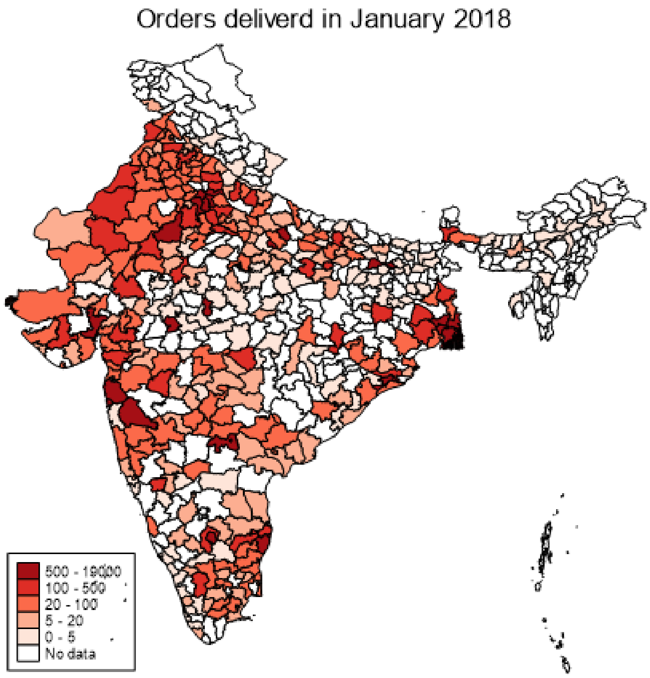


Figure 6: *Choropleth mapping of the number of orders by district in January 2018*



The drugs sold by 1mg are produced by 897 manufacturers, each producing on average 15 different salts and 16 different brands. See table nine in the appendix for a table with a ranking of the most ordered salts. Looking at the distribution of the number of brands available within a salt, the average salt is sold in 36 different brands. The salt with the highest number of brands is the combination of Domperidone and Pantoprazole, a drug within the gastro intestinal therapeutic usage category sold in 162 different brands. For the top 50 salts with the highest number of brands available, see table ten in the appendix.

From the 3.2 million drugs ordered in the timespan of the data, nearly 85% is for RX medication, while the other 15% accounts for over-the-counter medication. Additionally, 87% of orders have been medicines used for the treatment of chronic diseases. This was to be expected, since patients facing acute health issues will more likely visit a brick-and-mortar pharmacy because of time considerations, while patients suffering from chronic issues are able to plan their orders over time and choose for the ease of home delivery and price competitiveness of e-pharmacies. Corresponding with this logic, the top two most ordered therapeutic usage categories are aimed at chronic issues, with Cardiac and anti-diabetic medication accounting for a combined 56% of drugs ordered. See table eight in the appendix for the number of orders within each therapeutic usage category.

The order data of 1mg is specific on an order and drug level, meaning that even though an order can contain several drugs, each observation is drug specific and contains information about the formulation, its producer and price, therapeutic usage and classification of the drug ordered. User information is anonymized and limited, providing only the coded user id and the area code of the location the user made the order to be sent to.

In order to limit the analysis solely on orders that have actually been delivered and exclude any orders that have been returned or otherwise have not been consumed, we include only orders with a 'delivered' status. Additionally, orders with a missing salt-name have been excluded as they lack essential information.

Lastly, all orders of OTC medication have been excluded. The reason for only analysing orders of RX medication, is that people do not need a prescription to buy over-the-counter medication. Therefore, patients are free to choose the medicine brand of their choosing from the start, based on whatever preferences they have and all information available on 1mg. As such, analyses of the effect of decreased information asymmetries is made unmeaning, as there is no change to be observed.

4.2 Methodology

In order to answer the hypotheses, we will start by running a fixed-effects analysis of the effect of the number of orders on dosage price. In this analysis, the dependent variable dosage price is calculated as the price of the specific formulation of the drug ordered in Rupees (INR ₹), divided by the item size of the order, measured as for example the number of pills in a package.

The main explanatory variable is a sequence variable, which counts upwards for each order by a unique customer within a formulation of a drug. This formulation is specific to the salt, strength and drug form delivery method, in order to eliminate heterogeneity in all aspects besides the brand of the drug with that specific formulation bought by the user. By sorting the data on user id, salt, strength and drug form respectively, and ordering chronologically by order date, the sequence variable counts upwards chronologically for each order by a specific user within a specific formulation, starting from 1 with the first order. As with each order the user is exposed to price comparison of potential cheaper alternatives within the ordered formulation, we would expect the user to substitute to a cheaper formulation with increasing likelihood by each additional order. Consequently, as the dosage price should go down by substituting, we would expect the sequence variable to be negatively correlated to the dependent variable of dosage price.

An additional explanatory variable is the number of alternative brands available in a formulation of a drug. We will first incorporate this variable in the regression specified on a salt, strength and drug form specific formulation. Later, as a robustness check we will look at the effect of a more relaxed definition of the number of alternatives specified only on a salt and its strength, without specifying on drug delivery.

By using a fixed-effects regression, we are able to account for unobservable, time-invariant heterogeneity. In this regression, time-invariant heterogeneity is nested in unobserved factors of individual users, such as their age, gender, income, but also for example a user's degree of frugality, as well as in unobserved factors regarding the salt which is ordered, such as the complexity of the production process, whether the drug is meant for chronic or acute ailments, or the costs of the IPA. In order to account for unobserved time-invariant heterogeneity in salt and user id both at the same time, I have created a new variable which uniquely identifies every combination of user id and salt, by grouping salt name and user id. Assuming that all the unobserved factors remain the same over the timeframe a user has ordered medicine, allows us to observe the causal effect (p) of the increasing exposure to 1mg's price comparison tool measured by the main explanatory variable 'sequence' (T), on the dosage price (Y) a user (i) is paying at time (t).

Consequently, the regression formula looks as follows:

$$Y_{it} = \alpha_i + pT_{it} + \varepsilon_{it}$$

Where ε_{it} represents the individual error terms and the unobserved individual time invariant characteristics α_i are captured by ,

$$\alpha_i = \alpha + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_K X_{Ki}$$

each X_k being an unobserved time invariant variable and β_k being the individual's intercept for variable X_k.

Because there is very little heterogeneity among different brands of medicines within the same formulation of a salt, no other time variant variables to include in the regression are present in the data. However, in addition to the main explanatory variable sequence and the variable with the number of alternatives available, several controls will be added to the regression. In order to correct for the influence of seasonality of the economy and of for example the weather in India[10], month as well as year fixed effects are included. Additionally, drug form fixed effects are taken into account since specific drug delivery forms have different costs, as well as manufacturer fixed effects to account for firm heterogeneity.

Furthermore, in order to test the third hypothesis which states that chronic patients are more likely to substitute towards cheaper alternative brands compared to patients ordering medication for non-chronic issues, an interaction term of sequence and a dummy for chronic medicines is constructed and an additional fixed effects regression is run with this interaction term included. The variable is

[10] Every year in India, seasonal phenomena such as the monsoon cause a rise in fever and other conditions.

constructed by multiplying the value of sequence with the value of the dummy for chronic, which is either 1 in the case of chronic medicines or 0 for non-chronic medication.

Subsequently, to increase the robustness of the results, the regressions will be run on several different samples to test the effect of sequence under varying selections and definitions of variables will be relaxed.

Finally, in order to verify the results of the econometric analysis, several metrics will be plotted over the time the dataset spans in the descriptive evidence section as a robustness check and to test hypotheses 4a trough 4d.

5. Results:

5.1 Econometric evidence

In order to estimate the effect of the decreasing information asymmetry with each additional order, we start by building the regression model, adding variables step by step and running a fixed effects regression on the full sample of all RX orders. The results are displayed in the table below.

Table 1: *Fixed effects regressions on full sample of RX medication*

	(1) Dosage Price	(2) Dosage Price	(3) Dosage Price	(4) Dosage Price	(5) Dosage Price
Sequence	0.270***	-0.170***	-0.170***	0.0343***	0.0341***
	(0.0213)	(0.00466)	(0.00466)	(0.00729)	(0.00728)
Alternatives available			-0.0186***	-0.0190***	-0.0195***
			(0.00174)	(0.00174)	(0.00181)
Constant	28.14***	30.21***	31.31***	31.61***	82.23***
	(0.175)	(0.0269)	(0.106)	(0.585)	(12.93)
Observations	2,090,927	2,090,927	2,090,927	2,090,927	2,090,927
Adjusted R-squared	0.000	0.984	0.984	0.984	0.984
User and Salt FE	No	Yes	Yes	Yes	Yes
Time FE	No	No	No	Yes	Yes
Manufacturer FE	No	No	No	No	Yes
Drug form FE	No	No	No	No	Yes

*Note. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1*

In the first column of table 1, the results of an ordinary least squares (OLS) regression of sequence on dosage price are shown. Although the coefficient for sequence is positive and significant, an OLS regression does not fit this regression as it does not account for unobserved heterogeneity, which explains the very low explanatory power of the model as displayed in the low adjusted R-squared. However, if we use a fixed effects regression and control for user and salt unobserved heterogeneity as discussed in the methodology, the explanatory power increases greatly. The coefficient in this second regression is negative and significant, which would suggest that the dosage price a patient has to pay decreases with every additional order he makes on 1mg. If we add the control variable of the number of alternatives available, the coefficient and significance of the sequence variable does not change. The coefficient of alternatives available is negative and significant as suspected, suggesting that the more alternative brands are available in a formulation, the lower the dosage price a user has to pay will be.

In regression 4 and 5, time fixed effects consisting of month and year effects, and manufacturer and drug form fixed effects are added respectively. Even though the Adjusted R-squared does not change when these fixed effects are added, the sign of the sequence variable changes from negative to positive, suggesting that the more often a user orders a medicine within a certain formulation the higher will be the dosage price. Apparently, controlling for seasonality corrects an omitted variable bias as the time fixed effects account for a big part of the heterogeneity in dosage prices. Lastly, when adding manufacturer and drug form fixed effects the precision of the model is increased further as the coefficients change with tiny fractions. The constant is the only coefficient that changes significantly, while the other coefficients' interpretations and significance levels remain the same.

As the regression above was run on the total sample of all RX orders by all users, it included also many observations in which customers bought a specific formulation of a drug at least once, but have not substituted within that formulation. This might have an impact on the strength and direction of our main explanatory variable of sequence. Therefore, we will also run the same regression model on a sample containing only users who have substituted at least once, to see if the substitutions that occur result in lower dosage prices. The results of this regression are presented below in table 2.

Table 2: *Fixed effects regressions on substituting users only*

	(1) Dosage Price	(2) Dosage Price	(3) Dosage Price	(4) Dosage Price	(5) Dosage Price
Sequence	-0.0399	-0.0688***	-0.0688***	-0.00120	-0.00524
	(0.0266)	(0.0108)	(0.0108)	(0.0160)	(0.0151)
Alternatives available			-0.00352	-0.00367	-0.000181
			(0.00480)	(0.00480)	(0.00568)
Constant	18.90***	19.07***	19.42***	21.45***	14.59
	(0.349)	(0.0808)	(0.477)	(1.096)	(11.28)
Observations	135,966	135,966	135,966	135,966	135,966
Adjusted R-squared	0.000	0.967	0.967	0.967	0.971
User and Salt FE	No	Yes	Yes	Yes	Yes
Time FE	No	No	No	Yes	Yes
Manufacturer FE	No	No	No	No	Yes
Drug form FE	No	No	No	No	Yes

*Note. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1*

Again, in the second and third regressions, the coefficients of our main variable of interest are negative and significant, although small. This time however, the number of alternative available seems irrelevant as the coefficient is insignificant and very small. When seasonality is accounted for by including time fixed effects in column four, the coefficient of sequence becomes even smaller in size and loses its significance. Adding manufacturer and drug form fixed effects only significantly changes the constant. In conclusion, even in a sample with only users who have substituted, the results do not provide evidence for the hypothesis of decreasing prices with increasing orders.

Another interesting sample selection, is to focus only on the most sold salts formulations in regard of salt and strength. As these salts are ordered the most, they are arguably the medicines with the highest exposure of price comparison on the 1mg platform, seen by the biggest number of people and most frequently. In these top sold medicines therefore, the information asymmetry decrease regarding prices and alternatives, should be the biggest. By filtering the sample of all RX orders on the top 50 most frequently ordered salts and running the regression again, we get the following results:

Table 3: *Fixed effects regressions on top 50 most sold salts*

	(1) Dosage Price	(2) Dosage Price	(3) Dosage Price	(4) Dosage Price	(5) Dosage Price
Sequence	0.155***	-0.0859***	-0.0856***	0.0464***	0.0460***
	(0.00665)	(0.00403)	(0.00403)	(0.00638)	(0.00637)
Alternatives available			-0.0219***	-0.0221***	-0.0222***
			(0.00130)	(0.00129)	(0.00135)
Constant	15.97***	17.16***	18.88***	19.27***	17.53**
	(0.0529)	(0.0242)	(0.105)	(0.557)	(8.467)
Observations	1,168,452	1,168,452	1,168,452	1,168,452	1,168,452
Adjusted R-squared	0.000	0.875	0.875	0.875	0.876
User and Salt FE	No	Yes	Yes	Yes	Yes
Time FE	No	No	No	Yes	Yes
Manufacturer FE	No	No	No	No	Yes
Drug form FE	No	No	No	No	Yes

*Note. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1*

Again, the sequence variable is not what we expected it to be. The coefficient of the variable starts of negative and significant, but as soon as we control for seasonality, the sign changes to positive. Adding manufacturer and drug form fixed effects does not alter these results. Therefore we can conclude, that even in the sample with the most frequently bought medicines and therefore the highest exposure to 1mg's price comparison tool, the dosage price does not seem to decrease with the number of orders. The coefficient in this sample for the number of alternatives however, remains negative and significant in all model specifications the variable is included.

A last sample selection which is worthwhile to analyse, is a sample of the medicines with the highest number of alternatives available. Since these medicine should arguably have the biggest dispersion in prices, there is the most room for price substitution. The result of the regression run on the 50 salts with the highest number of alternatives available is presented in table four.

Table 4: *Fixed effects regressions on the top 50 salt with most alternatives available*

	(1) Dosage Price	(2) Dosage Price	(3) Dosage Price	(4) Dosage Price	(5) Dosage Price
Sequence	-0.0409***	-0.000335	-0.000196	0.00359***	0.000506
	(0.00206)	(0.000556)	(0.000538)	(0.000867)	(0.000664)
Alternatives available			-0.0315***	-0.0315***	-0.0660***
			(0.000284)	(0.000284)	(0.000336)
Constant	8.228***	8.045***	15.11***	15.42***	26.98***
	(0.0203)	(0.00307)	(0.0637)	(0.0858)	(0.202)
Observations	234,544	234,544	234,544	234,544	234,544
Adjusted R-squared	0.001	0.985	0.986	0.986	0.992
User and Salt FE	No	Yes	Yes	Yes	Yes
Time FE	No	No	No	Yes	Yes
Manufacturer FE	No	No	No	No	Yes
Drug form FE	No	No	No	No	Yes

*Note. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1*

Even though in this sample selection the opportunities for substituting and costs savings are highest, the coefficient of sequence becomes positive and statistically significant as soon as we add time fixed effects. However, when also adding manufacturer and drug form fixed effects, the coefficient loses its significance, besides being very small. Therefore, the effect of more orders on dosage price in this sample selection is indistinguishable from zero.

Based on the results of the regression model on these four different samples, we have to reject the first hypothesis that states that the higher the number of orders a user of 1mg places within a certain medicine formulation, the lower the dosage price he has to pay becomes.

On the other hand, if we look specifically to the effect of the number of available alternatives, we can accept hypothesis two which stated that the higher the number of available alternatives, the lower the dosage price a patient has to pay will be. In three out of the four samples, the samples that also included users who ordered at least two times within a certain formulation of a salt without substituting, the coefficient for alternatives is negative and significant. This suggests that the higher the number of alternatives available, the lower the dosage price of medicines ordered.

However, in the sample with only substituting users included, the coefficient for the number of alternatives was insignificant and positive, as can be seen in table two. This suggest that when it comes to substituting, a higher number of alternatives available in a specific salt formulation does not lead to lower dosage prices. Moreover, in the regression run on the sample with the 50 salts with the most alternatives available (results displayed in table 4), the sequence variable is positive and insignificant. These insights combined, lead us to the conclusion that a high number of available alternatives is not enough to persuade customers to substitute towards cheaper alternatives. Thus, instead of users substituting because a high number of alternatives is available, the negative and significant coefficient of the number of alternatives available, might be explained by simple economic theory which argues that competition increases with additional producers, resulting in lower prices. Therefore, even though hypothesis two might be accepted, the reason for lower dosage prices with higher number of alternatives available does not seem to be derived from the explanation given in formulating the hypothesis. More specifically, users having more opportunities to substitute when there are more alternative brands available, does not seem to result in those users using these opportunities to substitute towards a cheaper brand.

In order to prove or reject the third hypothesis, stating that patients buying medication for chronic usage are more likely to substitute to a cheaper brand within a salt formulation, we add an interaction variable between sequence and the dummy for chronic medication to the most complete regression model. In this regression, we include the interaction term without including the chronic dummy individually, as the value of the dummy does not vary within the grouped observations since sequence is defined on a salt level, and a salt is either meant for chronic ailments or is not. Since this dummy therefore is time-invariant and does not change within observations, it would not make sense to include the individual term of chronic in the fixed effects model. The results of the regressions of the effect of sequence on dosage price with the specified interaction variable included, run on the full sample as well as on two new samples, are displayed in the table five, presented below.

Table 5: *Full fixed effects model with chronic-sequence interaction on different samples*

	Full Sample	Chronic sample	Non-chronic
Sequence	0.175***	0.0276***	0.145***
	(0.0240)	(0.00758)	(0.0230)
Alternatives available	-0.0195***	-0.0169***	-0.124***
	(0.00181)	(0.00185)	(0.00903)
Chronic-Seq interaction	-0.149***		
	(0.0240)		
Constant	82.27***	19.17	143.1***
	(12.93)	(15.21)	(22.41)
Observations	2,090,927	1,962,905	128,004
Adjusted R-squared	0.984	0.970	0.999
User and Salt FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Manufacturer FE	Yes	Yes	Yes
Drug form FE	Yes	Yes	Yes

*Note. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1*

In the full sample, the variable displaying the interaction of sequence and chronic is negative and significant. This result indicates that patients buying medicine for chronic issues, pay .149 INR less for each dosage with every increase in sequence (every additional order), compared to patients ordering non-chronic medication. As the fixed effects regression accounts for price differences between salts and for price differences between users who are prescribed differently specified formulations, this dosage price decrease can be contributed to chronic medication ordering users substituting towards cheaper alternatives more than users who order non-chronic medication. Therefore, we can accept hypothesis three, stating that chronic patients are more likely to substitute to a cheaper brand within a salt formulation.

However, even though the regression results of the full sample displayed in the first column of table 5 show that chronic users pay .175 INR less with every additional purchase, the residual effect of sequence and the interaction term combined remains positive[11]. This tells us that patients buying chronic medication still face increasing dosage prices with every additional order, even though this increase in dosage price is lower than for patients buying non-chronic medication.

To test this conclusion, we also run the previously specified full regression model on a sample with only orders for chronic medication, as well as on a sample of orders of only non-chronic medication. The results of these regressions are displayed on the right hand side of table 5 and are consistent with the conclusion stated earlier, as the sequence variable in both samples is positive and

[11] If we subtract the decrease in dosage price for chronic patients from the positive coefficient of sequence, we are still left with a price increase with each dosage of .175-.149=.026 INR.

significant, while the coefficient of sequence in the chronic sample is considerably smaller than in the non-chronic sample. Patients ordering medication for chronic issues therefore still face increasing costs with each additional order, indicating that there is still not enough substitution towards cheaper brands happening to have a lowering effect on dosage prices with each additional order.

5.2 Robustness checks

There are some additional analyses we can do to check the robustness of the previously discussed results. First of all, taking the natural logarithm of dosage price, might make the distribution of the variable conform better to the normal distribution, and therefore yield better results in analysis. The result of the full regression model run on the natural logarithm of dosage price is presented below in the first column of table six. See tables 11 trough 14 in the appendix for all regressions run on the 4 different model specifications

Table 6: *Full sample fixed effects regressions with different variable specifications*

	(1) LN of Dosage Price	(2) Dosage Price	(3) Dosage Price	(4) LN of dosage price
Sequence	0.00103***			
	(3.51e-05)			
Sequence Salt & Strength		0.0377***	0.0381***	0.000978***
		(0.00729)	(0.00729)	(3.51e-05)
Alternatives available	-0.000884***	-0.0195***		
	(8.70e-06)	(0.00181)		
Alternatives Salt & Strength			-0.0124***	-0.000647***
			(0.00115)	(5.54e-06)
Constant	3.074***	82.33***	81.98***	3.061***
	(0.0623)	(12.93)	(12.93)	(0.0622)
Observations	2,090,927	2,090,927	2,090,927	2,090,927
Adjusted R-squared	0.992	0.984	0.984	0.992
User and Salt FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Manufacturer FE	Yes	Yes	Yes	Yes
Drug form FE	Yes	Yes	Yes	Yes

*Note. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1*

As we can see, log-transforming the dependent variable has not changed the analysis results significantly. The coefficient of sequence in the full regression model remains positive and significant as well as nearly indistinguishably small. The interpretation of a log transformed variable is slightly different however, as in log-level regressions, one additional unit of the continuous independent variable x increases the log transformed dependent variable y by 100*(exp(βX)-1)%. Therefore, according to this regression, each additional unit of sequence, or with every extra order, the dosage price increases with 100*(exp(0.00103)-1)= approximately .1%.

Another thing we can do, however, is to relax the definition of sequence. Instead of having sequence counting upwards specified on orders within the same salt, strength and drug form, we can loosen this specification to salt and strength. This way, sequence remains counting upwards when a user switches drug form, from example switches from a tablet to a capsule, within the same salt and strength, instead of the sequence variable starting over when a user switches drug form. However, as can be seen from the results displayed in the second column of the previous table, this relaxed definition of sequence changes very little in terms of sign and significance compared to the results of the full regression model run on the more stringent definition of sequence. The fact that relaxing the definition of sequence does not alter the results significantly, is probably due to the fact people do not often switch drug forms within a certain salt and strength.

Furthermore, an additional definition we can relax is the one of the number of alternatives available. Like the original sequence variable, this variable was specific to a salt, strength and drug form level. However, if we relax this definition to specify only on salt and strength, the number of alternatives available to a patient within a formulation are often increased, as formulations of the same salt and strength but a different kind of tablet, are now also counted as an available alternative. The results of this analysis with a relaxed definition for sequence and the relaxed definition of the number of alternatives both, is presented in the third column of table six.

Compared to the regression results in the previous column, not much has changed. If anything, relaxing the definition of the number of alternatives has decreased the effect, as the coefficient is slightly less negative than before. The coefficient remains negative and significant however, suggesting that the more alternatives are available within a specification; the lower will be the dosage price.

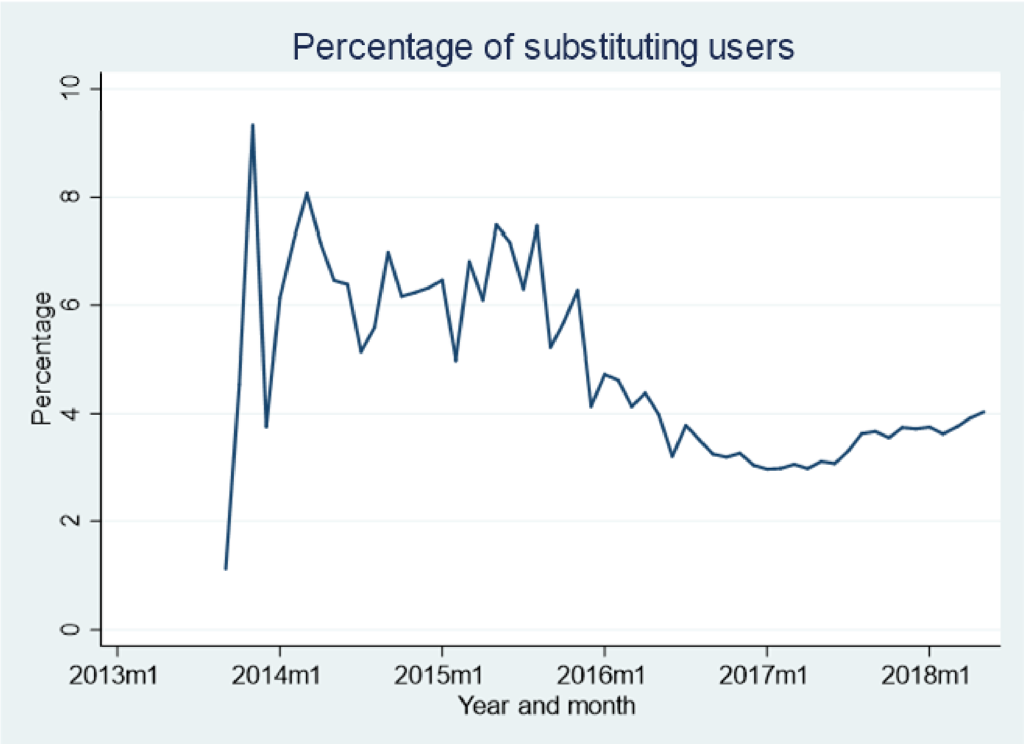
Finally, we can do a last robustness check of the main analysis by running the full regression model with all these relaxed definitions of dependent and independent variables on the natural logarithm of dosage price. The results of this regression are displayed in the final column of table six. Even with all definitions relaxed, the coefficient of sequence is still insignificant and positive instead of negative. The interpretation of the (relaxed) sequence variable is again an approximate .1% increase in dosage price with every additional order.

5.3 Descriptive evidence

Besides the econometric analysis described in the section above, we can also examine the effect of 1mg providing information to decrease the information asymmetry regarding medicine prices visually, by looking into the number of different occurrences of substitutions over time. As described while formulating hypotheses 4a through 4d, we would expect several different aspects of substitutions taking place to increase (or decrease) over the six years available in the data as 1mg matures and gains popularity among the Indian population.

Starting with hypothesis 4a, which stated that the number of substitutions should increase over time, the monthly number of users who substituted within their salt as a percentage of the total number of users ordering on 1mg per month, are plotted in the figure eight below.

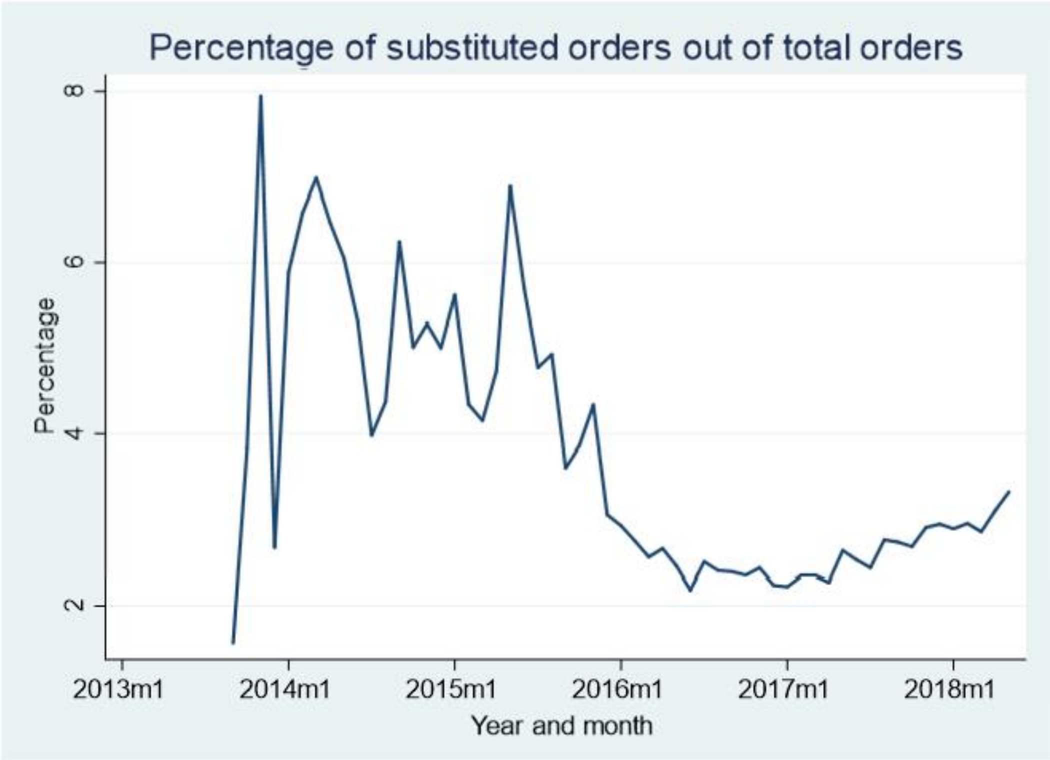
Figure 8: *The percentage of substituting users out of total monthly users*



While we would expect this share to increase over the time 1mg is operating, there is no clear trend to be seen. Besides the explanation that the ratio just is not growing over time, the ambiguous trend in this plot might be due to unevenly distributed growth shocks of the number of users ordering on 1mg, as new users are not yet familiar with the price comparison tool offered by the platform.

Likewise, if we look into the ratio of substituting orders instead of users, by plotting the number of substituting orders, defined as the first order by a user after substituting towards a different brand, as a share of total monthly orders in figure nine, no increasing trend can be observed. While it is more likely that the ratio of substituting orders is just not increasing, the same reasoning of unevenly distributed growth shocks might explain the lack of an increasing trend in the plot.

Figure 9: *The percentage of substituted orders out of total monthly orders*



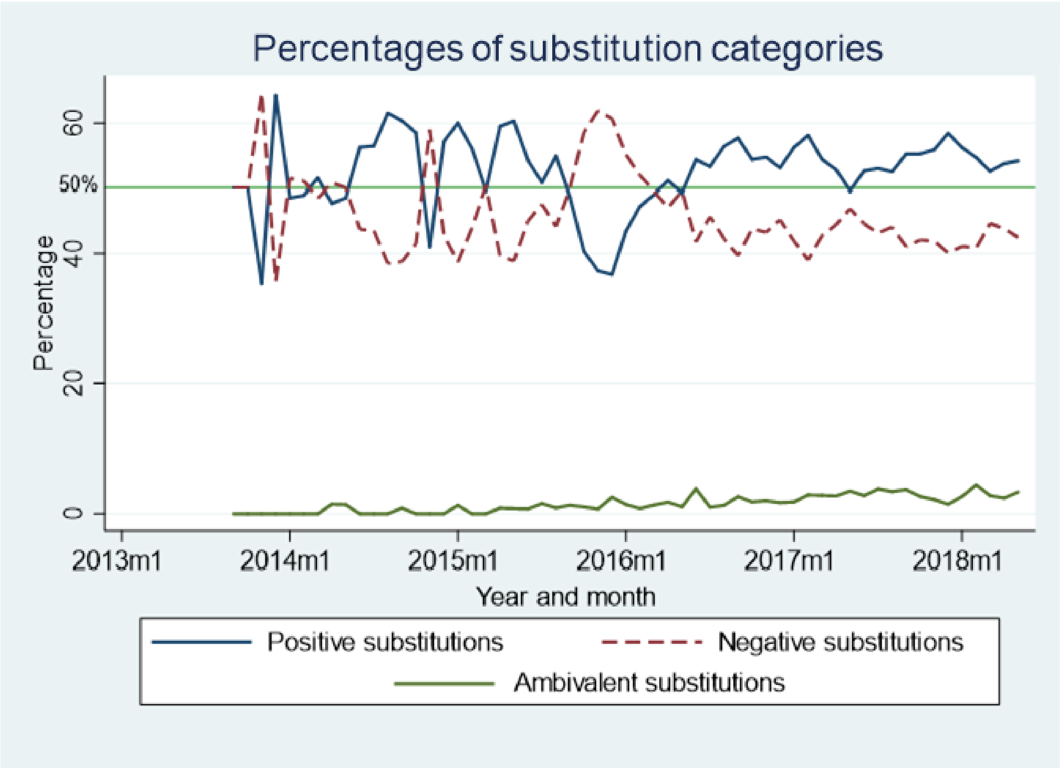
When looking at the number of substitutions however, we can differentiate between substitutions towards a cheaper alternative (positive substitutions), substitutions towards a higher priced alternative (negative substitutions), or substitutions towards an alternative with an equal price (ambivalent substitutions). As argued while formulating hypothesis 4d, a substitution towards a cheaper alternative is arguably driven by economic reasons, while a substitution towards an equally priced or more expensive alternative will most likely be driven by dissatisfaction with the efficacy or other factors of the previously prescribed brand, or by doctor's directions. The frequency of each substitution occurrence by these categories is displayed in table seven.

Table 7: *Categories of substitutions and their occurrences*

Substitution direction	Frequency	Percent
Positive Substitutions	13,853	53.79%
Negative Substitutions	11,239	43.64%
Ambivalent Substitutions	660	2.56%
Total	25,752	100.00%

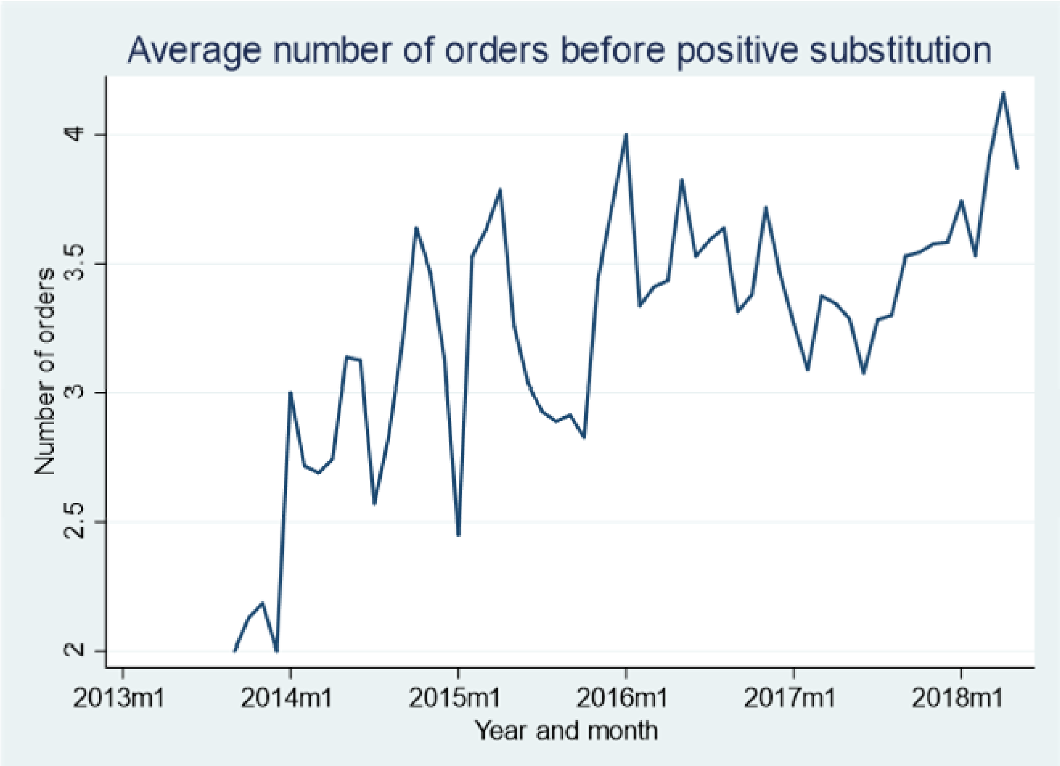
As can be seen in the table, positive substitutions make up the larger share of substitutions. If we plot the share of these respective substitutions for each month during the time of the dataset, we can see that there is no clear trend, not to mention an increasing trend of positive substitutions as a share of total substitutions. This is the case as both negative and positive substitution shares circle around each other on the 50% reference line, as can be seen in figure ten presented below.

Figure 10: *Share of substitutions by category over time*



Finally, by making the distinction in positive and negative substitutions, we can look into the number of orders a user places before substituting towards a cheaper alternative. From the logic explained in formulating hypothesis 4d, we would expect this number to decrease over time. As familiarity with the 1mg price comparison tool and awareness of the possibilities of costs savings among the frugal Indian population increase over time, we should be able to see a decline in the number of orders users make of their originally prescribed expensive brand before substituting towards a cheaper alternative. However, if we plot the average number of orders customers made before substituting towards a cheaper brand, in the month the first order of the substituted, cheaper brand was made over time, we see an increase in the number of orders users place of their originally prescribed brand, instead of a decreasing trend.

Figure 11: *Monthly average of the number of orders before substituting towards a cheaper alternative*



In conclusion, based on the visual evidence presented above taken together, we have to reject hypotheses 4a through 4d, as there is no increase in users substituting towards cheaper alternative brands over time.

Therefore, based on all econometric as well as descriptive evidence, we can unfortunately only conclude that the decrease of the information asymmetry regarding alternative brands and their prices within a specific salt formulations facilitated by 1mg, does not lead to its users substituting towards cheaper alternatives and decreasing their costs of medicines.

6. Discussion and recommendations:

6.1 Discussion of results

While the results are not as expected from the theoretical framework, there are several reasons that could provide an explanation.

First of all, the econometric analysis might be flawed due to several reasons. One of those reasons is that a fixed effects regressions does not account for unobserved individual shocks. For example, if the income of a user increases between orders, he might be less motivated to substitute towards a cheaper alternative, or even substitute towards a more expensive brand because of personal preferences. Likewise, there could be unobserved shocks to the prices of medicine by a certain manufacturer after encountering problems with a supplier. However, considering the large number of observations the regressions are based on, these potential unobserved shocks are unlikely to effect the results much.

A second problem with the analysis, is a lack of (reliable) data. Besides the fact that there might be some inaccuracies in the data, resulting in for example an overestimated dosage price for medicines in syrup or cream formulation due to the difficulty of calculating a dosage price for such formulations, there are several variables missing in the analysis which might have led to skewed results. For starters, we have no information on individual patient characteristics such as their age and income, which could have been used to distinguish between young, tech-savvy users likely to make full benefit of the technological benefits of ordering on 1mg and older users, as well as distinguishing between affluent and poor users. Also, we have no data on the reasons why users have substituted. Knowing the reason for the substitution by a specific user, such as advise from his doctor, disliking of his current medicine, his preferred medicine being out of stock or because he actually wanted to lower the costs of medicine, would have allowed for more reliable analysis.

Additionally, I do not have data on occurrences of patients getting back to their doctor to ask for a cheaper prescription. Since we lack data on users trying to get a new prescription from their physician, we do not know how many have tried and failed, or how many succeeded. Having data on these occurrences would allow us to better estimate the effect of the information provided by 1mg, as well as to better contribute the lack of results to either doctors not cooperating or other factors. Additionally, with regard to the effect of the number of alternatives available within a salt, we should note that this number is time invariant, as the descriptive data on all medicines sold by 1mg is not panel data showing growth or decline of the offering of brands on 1mg over time, but rather cross sectional data of the offer available as of June 2018. Because the number of available alternatives on

1mg at the end of the data is used for analysing the entire period of the data, the effect of the number of alternatives available on dosage prices and substitutions might have been over- or underestimated. This depends on whether more or less brands were available within a certain salt at specific times in the period the data spans compared to at the end of the data.

Another possible way in which the analysis results may be flawed, is that we assume that the information asymmetry regarding prices is decreased with every order because of the exposure to 1mg's price comparison tool. However, it may be the case that a patient does not read this information every time, or even ever, but just orders his prescribed medicine immediately, without being exposed to the information meant to decrease the information asymmetry. Not accounting for this might have caused an over-estimation of the decrease in the information asymmetry brought about by 1mg. Finally, it would also have been useful to have data on the pharmaceutical producers incentivizing doctors to prescribe certain brands.

Notwithstanding these critical notes, the econometric analysis has been run on several different samples and all results reject the first hypothesis. Besides, even when the econometric analysis might be skewed, the descriptive evidence presented is quite clear. Therefore, it is evident that the decreased information asymmetry realised by 1mg's price comparison tool does not lead to an increase in patients substituting towards cheaper brands of medicine and lowering their costs of medication.

The most important explanation for this conclusion is the lack of freedom for patients to choose a brand within the formulation of a salt prescribed by their physician. Even though the information asymmetry regarding available alternatives and their prices created by doctors prescribing brands instead of salts is eliminated by the price comparison provided by 1mg, the transaction costs of trying to get a new prescription for a cheaper alternative appear to be too high. Because of this, the huge potential for savings on the costs of medicine are not realised. At the same time, with the transaction costs of substitution being this high, promotion of substituting through word of mouth will be significantly less than expected. This will result in a lower dispersion of awareness for the possibility of substituting. Lastly, an inhibiting factor for the realisation of substitutions might be patient conservatism and greater risk sensitivity due to the high stakes of healthcare. Patients are likely less willing to take chances when it comes to their health of the health of their loved ones, and will therefore rather listen to their physician and buy the expensive brands prescribed instead of trusting on a lesser known brand without the doctor's approval. Besides, the low awareness among the relatively uneducated population of India on the fact that every brand of medicine across a formulation has the exact same API and should therefore yield identical results, hinders substitution.

6.2 Policy recommendations and future research

Based on the research and the results presented in this paper, I have formulated a couple of policy recommendations. Firstly, in order to realise the full potential of cost savings enabled by e-pharmacies such as 1mg, providing information on cheaper alternative brands is not enough when the effort needed to realise these costs savings is too high. Therefore, instead of needing to get back to and argue with their doctor in order to get a cheaper prescription for a medicine, patients should be able to select and purchase a brand of their choosing within the prescribed formulation of a salt themselves. This could be achieved by implementing regulations that require physicians to prescribe a formulation of a salt, instead of prescribing specific brands. The freedom for patients to choose brands themselves can naturally only be extended to patients if all pharmaceutical producers are subject to the same strict safety and quality regulations with audits and regular checks, and medicine safety is guaranteed.

An alternative approach to alleviate the problem of expensive medication, would be to regulate the Indian pharmaceutical market's dynamics conform the European system, where health insurance companies, pharmaceutical producers and doctors coordinate prescriptions within a triangular relationship. In this system, health insurance companies look into the portfolio of brands within a salt, and select the brand with the best price to be reimbursed in their insurance. This means that pharmaceutical producers compete fiercely over the designation to be reimbursed in health insurance, with lower prices as a result of this competition. Patients who wish to take a different brand then prescribed by default, can request so with their doctor, but will have to pay for the medicine themselves. Additionally, doctors have to conform to a maximum budget they can use to prescribe non-reimbursable brands to patients. With this system, the power of pharmaceutical producers to incentivize doctors to prescribe their brands, and therefore the incentives for doctors to prescribe these expensive brands to their patients, is reduced significantly. However, since health insurance in India is not obligatory and market penetration is very limited, alongside other institutional voids present in the healthcare sector, the effort and costs to implement a system as such seem way too big at this time. Therefore, the first policy recommendation is to be preferred as it is likely to yield results sooner and more efficiently.

In order to shine more light on the topic presented in the thesis, I have several future research recommendations. First of all, it would be a useful addition to this research to look into the reasons why customers of 1mg have substituted, for example through a survey. Finding out in detail what drives or what hinders patients to substitute between brands, will be useful in designing regulations aimed at lowering the costs of medicine.

Additionally, prime minister Modi already announced to change regulations regarding medicine prescriptions by enforcing doctors to prescribe salts instead of brands, back in April 2017 (Dey, 2017). When this regulation is finally implemented, it would be interesting to repeat this research and see whether the change in regulation leads to a further decreased information asymmetry and results in patients being able to get cheaper medicine.

Lastly, it would be interesting to see whether the easy price comparison facilitated by e-pharmacy platforms such as 1mg, will lead to higher competition among pharmaceutical producers and therefore lower prices of medicines in the long term, as economic theory suggests.

Even though the price comparison tool provided by 1mg does not lead to users substituting their prescribed medicines for cheaper alternatives, there are several other benefits to the platform business model worth mentioning. First of all, the move of offline towards online commerce results in higher transparency throughout the sector's value chain. This reduces the opportunities for intermediaries up the supply chain to temper with packaging and commit fraud by, for example, selling fake medication. Additionally, because of the same transparency of transactions, e-commerce platforms are unable to sell RX medication to users without a fully correct prescription as these illegal transactions would be easily picked up in audits. This is specifically beneficial for patients, as patients with for example an expired prescription are forced to return to their physician and request a new one, giving the physician the opportunity to adjust the prescription if needed on the patient's most recent health developments, ultimately leading to better health outcomes for patients.

Additionally, platforms like 1mg enjoy the benefits of market insights distilled from their order data. These insights, among a plethora of other possibilities, allow e-pharmacies to identify product categories, such as the market for thermometers, in which products are too highly priced, or where there is a lack of market leadership or reliable producers. They are then able to step into this product category themselves with their own brand, if they so wish, and gain market leadership by leveraging their brand name and promoting their own products on the platform. Arguably, this is beneficial to the general population since the product offering and competition in the product category are increased.

A third benefit of the e-pharmacy model, are improved patient outcomes resulting from the created possibilities of partnerships between e-pharmacies and other players in the health sector. For example, the digitized transactions in e-pharmacies open up the possibility for health insurers to increase market penetration by forming partnerships with companies like 1mg. When all expenditures on medication are done through 1mg, the operational costs to the insurer, in regard to fraud checks and consolidation of expenses, are decreased considerably. Likewise, hospitals can benefit from forming partnerships as well if they arrange for the procurement of their out-patient-department

(OPD) medication to be handled by one single e-pharmacy, instead of having to deal with a wide range of suppliers and the resulting costs from this coordination. Having a centralised medicine supply from an e-pharmacy, should reduce prices as well as occurrences of unavailability of medicines, and lead to more patients being able to purchase the medication prescribed to them.

Lastly, the digitization of the sector in an e-pharmacy, allows for the (future) implementation of technologies such as artificial intelligence (AI) and blockchain. Besides using AI to gain additional insights from data, the technology could for example be used in e-consults with chatbots who, by asking questions and analysing responses, can form an overview of the specifics of each case and categorize them. The doctor handling this e-consult is then saved time by not having to ask these questions himself, and can even be given advice by the AI on subsequent steps based on historical data of the actions taken by this doctor and his colleagues in comparable cases. The implementation of such technologies made possible by the platform business model in healthcare, has the potential to dramatically decrease the time a doctor spends on one patient and realise huge efficiency gains, alleviating the pressure of the discrepancy between the number of doctors needed and present in India.

The transfer to the digital economy and the online players facilitating her have rapidly transformed many markets, and even a traditional sector characterised by inertia like healthcare is surely to be transformed as well. With the ever-increasing number of internet-connected consumers, technological innovations gaining traction, decreasing costs of these technologies and people everywhere getting accustomed to rapid online transactions and increased comfort, it is merely a question of when the transformation will happen. At the moment, there is still resistance to digital commerce in the Indian pharmaceutical sector by traditional incumbents, for example by brick and mortar pharmacies in the All India Organization of Druggist and Chemist (AIOCD) (News 18, 2018). The AIOCD has been fighting e-pharmacies in court, arguing that e-pharmacies raise the risk of patients getting addicted to drugs by selling RX medication without proper prescription, and that e-pharmacies might sell fake, contaminated or illegal medicines. While these risk are just as likely or even more likely for offline pharmacies, due to a lack of transparency and traceability in the offline value chain, and even though lawyers argued that e-pharmacies do not stock or sell medicines themselves, but rather connect buyers with sellers through their online platform, the judicial body of the government has imposed bans and other restrictions on e-pharmacies on several occasions (Healthworld from the Economic Times, 2018; Indian Business Times, 2018). The AIOCD has even gone as far as pressuring the government and calling for a nationwide strike of over 25,000 brick and mortar pharmacies and wholesalers, denying the Indian population access to medication for a day, while laying blame on the online pharmacies (News 18, 2018).

However, the advantages gained by online platforms through aggregating supply and demand, economies of scale, data insights, possibilities for implementing new technologies, the resulting cost efficiencies and the level of service they can deliver, give platforms a competitive advantage strong enough to be sure that e-pharmacies are here to stay. Moreover, platforms have the ability to transform the market to a customer centred model and reduce costs, which is in the best interest of the Indian population. A 2016 rapport by the Federation of Indian Chambers of Commerce and Industry (FICCI) on e-pharmacies in India already argued that the growth of e-commerce and retail are complementary and reinforce each other and that by smartly leveraging technology, immense value can be created by e-pharmacies. The rapport further argues that "The benefits the e-Pharmacy model brings to consumers, who are the majority, should be the first priority of the Government. It is critical that the regulatory framework in the country be conceptualized keeping in mind the larger interests of the consumers in the country. If technology is available to cut the intermediary costs on medicines, it must be allowed to be used to its full potential as it will bring down the retail price of many drugs and benefit the middle-class, which is most impacted by the price hikes." (Federation of Indian Chambers of Commerce and Industry (FICCI) , 2016).

There are still many obstacles to overcome and changes in the regulatory system to be made, before the potential value of the platform business model in healthcare can fully be realised. However, when it does, there are huge costs savings to be gained in the costs of medicines, which is essential especially for the poor population of India currently being forced below the poverty baseline. Furthermore, as said by both founder and CEO of 1mg Prashant Tandon as well as COO Tanmay Saksena, the potential for future technologies to increase efficiency in the sector are enormous, and the market for e-pharmacies as well as 1mg has not even reached 1% of this potential (Tandon P. , On the future potential of 1mg, 2018; Saksena, 2018). The real impact e-pharmacies like 1mg will have on the Indian healthcare sector, highly depends on the government cooperating and remains to be seen, while the platform business model slowly but steadily takes over the world.

7. Conclusion

Platforms are changing the world rapidly in almost every sector, increasing (allocational) efficiency, asset utilization and competition, while decreasing search costs and prices by using mechanics enabled by digitization such as aggregation and dis-intermediation of the market and network effects. Especially in industries characterised by high information intensity, a high level of fragmentation and the presence of information asymmetries, the platform business model can realise major efficiency increases. However, the healthcare sector is still lagging behind in platform penetration as the traditional market has many complicating characteristics, while also being the sector with the highest need for reduced costs and increased efficiencies. From the case study of Indian e-pharmacy platform '1mg' presented in this thesis, it is clear that even though platforms can be very successful in reducing information asymmetries, apt regulations are necessary to be able to realise the full potential of the benefits the platform business model can provide to the population. Specifically in the case of 1mg, the Indian government should devise regulations that allow patients to purchase medicine brands of their own choosing within the specification of the medicine prescribed to them, as the analysis in this paper has proven that a decrease in information asymmetries regarding medicine brands and their prices by itself, is not enough to lower the price patients pay for their medicines.

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Appendix

Table 8: *Number of orders by therapeutic usage*

Therapeutic Usage of salt	Number of orders	Percentage
Anti Diabetic	686,694	22.18
Anti Infectives	50,543	1.63
Anti Malarials	89	0.00
Anti Neoplastics	24,237	0.78
Blood Related	6,564	0.21
Cardiac	1,066,218	34.45
Derma	224,175	7.24
Gastro Intestinal	223,707	7.23
Gynaecological	53,753	1.74
Hormones	47,753	1.54
Neuro Cns	199,287	6.44
Ophthal	81,536	2.63
Ophthal Otologicals	11,529	0.37
Others	10,375	0.34
Otologicals	525	0.02
Pain Analgesics	156,341	5.05
Respiratory	125,758	4.06
Sex Stimulants Rejuvenators	4,85	0.16
Stomatologicals	11,074	0.36
Urology	59,345	1.92
Vaccines	1,869	0.06
Vitamins Minerals Nutrients	49,199	1.59
Total	3,095,421	100.00

Table 9: *Number of orders by salt*

Salt name	Therapeutic Usage	Orders by Salt	Rank
Glimepiride+Metformin	Anti Diabetic	98677	1
Rosuvastatin	Cardiac	62617	2
Atorvastatin	Cardiac	56546	3
Metformin	Anti Diabetic	54453	4
Metoprolol Succinate	Cardiac	46194	5
Telmisartan	Cardiac	45090	6
Sitagliptin + Metformin	Anti Diabetic	44409	7
Metformin + Vildagliptin	Anti Diabetic	38649	8
Atorvastatin+Aspirin / Acetylsalicylic acid	Cardiac	33587	9
Aspirin / Acetylsalicylic acid	Cardiac	32971	10
Glimepiride	Anti Diabetic	26423	11
Teneligliptin	Anti Diabetic	23817	12
Aspirin / Acetylsalicylic acid+Clopidogrel	Cardiac	23547	13
Cilnidipine	Cardiac	23246	14
Glimepiride+Metformin+Voglibose	Anti Diabetic	22993	15
Amlodipine	Cardiac	22975	16
Ramipril	Cardiac	22002	17
Pantoprazole	Gastro Intestinal	21024	18
Telmisartan+Amlodipine	Cardiac	20609	19
Metformin+Teneligliptin	Anti Diabetic	20454	20
Voglibose	Anti Diabetic	19508	21
Thyroxine / Levothyroxine	Hormones	18979	22
Telmisartan+Hydrochlorothiazide	Cardiac	18796	23
Levetiracetam	Neuro Cns	18267	24
Insulin Glargine	Anti Diabetic	17919	25
Domperidone+Pantoprazole	Gastro Intestinal	17771	26
Olmesartan	Cardiac	17108	27
Clopidogrel	Cardiac	16737	28
Gliclazide	Anti Diabetic	16383	29
Febuxostat	Pain Analgesics	16076	30
Torasemide	Cardiac	15327	31
Carvedilol	Cardiac	14713	32
Sitagliptin	Anti Diabetic	14682	33
Vildagliptin	Anti Diabetic	14409	34
Gliclazide+Metformin	Anti Diabetic	14348	35
Empagliflozin	Anti Diabetic	14005	36
Fenofibrate+Rosuvastatin	Cardiac	13715	37
Glimepiride+Metformin+Pioglitazone	Anti Diabetic	13706	38
Nebivolol	Cardiac	12975	39
Insulin Isophane / NPH + Human Insulin / Soluble Insulin	Anti Diabetic	12674	40
Linagliptin	Anti Diabetic	11899	41
Losartan	Cardiac	11592	42
Nitroglycerin / Glyceryl Trinitrate	Cardiac	11323	43
Domperidone+Rabeprazole	Gastro Intestinal	11086	44
Aspirin / Acetylsalicylic acid+Atorvastatin+Clopidogrel	Cardiac	10870	45
Telmisartan+Metoprolol Succinate	Cardiac	10856	46
Progesterone (Natural Micronized)	Gynaecological	10750	47
Rosuvastatin+Aspirin / Acetylsalicylic acid	Cardiac	10634	48
Telmisartan+Chlorthalidone	Cardiac	10582	49
Dapagliflozin	Anti Diabetic	10479	50

Table 10: *Number of alternatives available by salt*

Salt name	Therapeutic Usage	Brands available	Rank
Pantoprazole	Gastro Intestinal	1013	1
Ofloxacin+Ornidazole	Gastro Intestinal	661	2
Ofloxacin	Anti Infectives	623	3
Domperidone+Rabeprazole	Gastro Intestinal	607	4
Azithromycin	Anti Infectives	601	5
Rabeprazole	Gastro Intestinal	546	6
Azithromycin	Anti Infectives	527	7
Amoxicillin + Clavulanic Acid	Anti Infectives	499	8
Domperidone+Pantoprazole	Gastro Intestinal	493	9
Cefixime	Anti Infectives	479	10
Levocetirizine+Montelukast	Respiratory	470	11
Levofloxacin	Ophthal	450	12
Cefpodoxime	Anti Infectives	425	13
Aceclofenac+Paracetamol / Acetaminophen	Pain Analgesics	410	14
Levocetirizine	Respiratory	381	15
Omeprazole	Gastro Intestinal	372	16
Amoxicillin + Clavulanic Acid	Anti Infectives	364	17
Cefixime	Anti Infectives	352	18
Ciprofloxacin	Gastro Intestinal	343	19
Fluconazole	Anti Infectives	328	20
Cefuroxime	Anti Infectives	323	21
Nimesulide+Paracetamol / Acetaminophen	Pain Analgesics	321	22
Domperidone+Pantoprazole	Gastro Intestinal	319	23
Ondansetron	Gastro Intestinal	311	24
Cefpodoxime	Anti Infectives	310	25
Diclofenac+Serratiopeptidase	Pain Analgesics	307	26
Domperidone+Omeprazole	Gastro Intestinal	303	27
Amoxicillin	Anti Infectives	297	28
Cefuroxime	Anti Infectives	295	29
Atorvastatin	Cardiac	285	30
Albendazole	Anti Infectives	266	31
Deflazacort	Hormones	261	32
Glimepiride+Metformin	Anti Diabetic	261	32
Glimepiride+Metformin	Anti Diabetic	256	34
Nimesulide	Pain Analgesics	255	35
Cetirizine	Respiratory	253	36
Methylcobalamin+Pregabalin	Neuro Cns	249	37
Piperacillin+Tazobactum	Anti Infectives	243	38
Amikacin	Ophthal	229	39
Progesterone (Natural Micronized)	Gynaecological	228	40
Metformin	Anti Diabetic	228	40
Telmisartan	Cardiac	226	42
Amoxicillin	Anti Infectives	220	43
Atorvastatin	Cardiac	218	44
Ciprofloxacin	Gastro Intestinal	216	45
Aceclofenac+Paracetamol / Acetaminophen	Pain Analgesics	215	46
Ceftriaxone+Sulbactam	Anti Infectives	213	47
Cefpodoxime+Clavulanic Acid	Anti Infectives	208	48
Diclofenac+Paracetamol / Acetaminophen	Pain Analgesics	208	48
Alprazolam	Neuro Cns	204	50

Table 11: *All regression models run on the natural logarithm of dosage price*

	(1) LN of Dosage Price	(2) LN of Dosage Price	(3) LN of Dosage Price	(4) LN of Dosage Price	(5) LN of Dosage Price
Sequence	0.0147***	-0.000287***	-0.000278***	0.00140***	0.00103***
	(0.000161)	(2.57e-05)	(2.56e-05)	(4.01e-05)	(3.51e-05)
Alternatives available			-0.00103***	-0.00103***	-0.000884***
			(9.59e-06)	(9.57e-06)	(8.70e-06)
Constant	2.248***	2.319***	2.379***	2.433***	3.074***
	(0.00113)	(0.000148)	(0.000584)	(0.00322)	(0.0623)
Observations	2,090,927	2,090,927	2,090,927	2,090,927	2,090,927
Adjusted R-squared	0.004	0.989	0.989	0.989	0.992
User and Salt FE	No	Yes	Yes	Yes	Yes
Time FE	No	No	No	Yes	Yes
Manufacturer FE	No	No	No	No	Yes
Drug form FE	No	No	No	No	Yes

*Note. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1*

Table 12: *All regression models run with the relaxed definition of sequence*

	(1) Dosage Price	(2) Dosage Price	(3) Dosage Price	(4) Dosage Price	(5) Dosage Price
Sequence Salt & Strength	0.258***	-0.168***	-0.168***	0.0362***	0.0377***
	(0.0210)	(0.00464)	(0.00464)	(0.00731)	(0.00729)
Alternatives available			-0.0186***	-0.0190***	-0.0195***
			(0.00174)	(0.00174)	(0.00181)
Constant	28.19***	30.21***	31.30***	31.67***	82.33***
	(0.175)	(0.0269)	(0.106)	(0.586)	(12.93)
Observations	2,090,927	2,090,927	2,090,927	2,090,927	2,090,927
Adjusted R-squared	*0.000*	*0.984*	*0.984*	*0.984*	*0.984*
User and Salt FE	No	Yes	Yes	Yes	Yes
Time FE	No	No	No	Yes	Yes
Manufacturer FE	No	No	No	No	Yes
Drug form FE	No	No	No	No	Yes

*Note. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1*

Table 13: *All regressions run with the relaxed definitions of sequence and the number of alternatives*

	(1) Dosage Price	(2) Dosage Price	(3) Dosage Price	(4) Dosage Price	(5) Dosage Price
Sequence Salt & Strength	0.258***	-0.168***	-0.168***	0.0366***	0.0381***
	(0.0210)	(0.00464)	(0.00464)	(0.00731)	(0.00729)
Alternatives Salt & Strength			-0.0115***	-0.0120***	-0.0124***
			(0.00113)	(0.00113)	(0.00115)
Constant	28.19***	30.21***	31.19***	31.61***	81.98***
	(0.175)	(0.0269)	(0.100)	(0.586)	(12.93)
Observations	2,090,927	2,090,927	2,090,927	2,090,927	2,090,927
Adjusted R-squared	0.000	0.984	0.984	0.984	0.984
User and Salt FE	No	Yes	Yes	Yes	Yes
Time FE	No	No	No	Yes	Yes
Manufacturer FE	No	No	No	No	Yes
Drug form FE	No	No	No	No	Yes

*Note. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1*

Table 14: *Regressions run with relaxed definitions of sequence and the number of alternatives on the natural logarithm of dosage price*

	(1) LN of dosage price	(2) LN of dosage price	(3) LN of dosage price	(4) LN of dosage price	(5) LN of dosage price
Sequence Salt & Strength	0.0142***	-0.000366***	-0.000358***	0.00125***	0.000978***
	(0.000160)	(2.56e-05)	(2.55e-05)	(4.02e-05)	(3.51e-05)
Alternatives Salt & Strength			-0.000646***	-0.000649***	-0.000647***
			(6.21e-06)	(6.20e-06)	(5.54e-06)
Constant	2.250***	2.319***	2.374***	2.426***	3.061***
	(0.00113)	(0.000148)	(0.000551)	(0.00322)	(0.0622)
Observations	2,090,927	2,090,927	2,090,927	2,090,927	2,090,927
Adjusted R-squared	0.004	0.989	0.989	0.989	0.992
User and Salt FE	No	Yes	Yes	Yes	Yes
Time FE	No	No	No	Yes	Yes
Manufacturer FE	No	No	No	No	Yes
Drug form FE	No	No	No	No	Yes

*Note. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1*