Pandemic Shock and Technology Replacement: Evidence from EMR Data on High-end Medical Treatment in India [*]

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Abstract

New technology adoption is driven by a troika – demand-pull, technology-push, and institutions shaped by market and non-market forces. In technologically laggard countries, often this process is slowed due to frictions arising from the fact that the new technology has to replace an established older technology. In this paper, we exploit the COVID-19 pandemic shock to examine how intra-organization technology replacements occurred due to concurrent shifts in the demand and the supply side. Specifically, we focus on the adoption of a high-end medical technology, Optical Coherence Tomography Angiography (OCTA), by ophthalmologists to diagnose prevalent eye diseases – replacing less costly and older technology OCT. We use novel Electronic Medical Records (EMR) data from one of the largest eye-care hospital chains in India that treats both non-paying and paying patients with a not-for-profit orientation. In a difference-in-differences setup, we consider non-paying patients as the treatment group and paying patients as the control group. We find that visual acuity among the pool of non-paying patients worsened during lockdown. Demand-pull generated through increased impairment propelled OCTA adoption by 21.6% points, predominantly facilitated through technology-push by young physicians. Higher adoption of OCTA, in turn, contributed to improving the eyesight of the non-paying patients. Our results go through various robustness checks and we conclude discussing the managerial and policy implications of our findings.

Keywords: Technology Adoption, Healthcare, Pandemics, Nonprofit Organizations

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1 Introduction

How does the scissor of demand and supply affect the timing of technology adoption? As Rosenberg (1972) famously noted – technology adoption can often be very slow and the rates of acceptance vary widely. There are proximate reasons for this. Demand for technology may be low due to lack of usage or a lack in perceived value of the technology, although the supply can be there. Supply of technology may be low due to the time required to develop or borrow the technology, while the demand can be there. Alternatively, the institutional ecosystem may influence both demand and supply due to market and non-market factors. There is no single answer to this question. Actors on both sides of the market may potentially play a role. Prior evidence here provides a broad spectrum of possible mechanisms. One set of extant research argues that the presence of economic incentives and profitability determines the pace of technology adoption (Griliches, 1957). Another stream of work posits that the extent of replacement of any technology depends on the characteristics of decision-makers, their networks, and the interactions within this network (Rogers *et al.*, 2014; Skinner & Staiger, 2009). An answer to the above question will also shed light on an associated puzzle – how managers and social planners can ensure that a given technology gets rapidly adopted.

Technology adoption is even more complex in a context like healthcare which is riddled with high degree of uncertainty and information asymmetry (Arrow, 1978). In addition, welfare consequences of technology adoption is often unclear given variation in organizational ownership and competition dynamics (Gaynor & Vogt, 2003). Further, there are variations in the mechanisms involved through which technology enhances welfare, be that, more generally, in adoption of productivity-increasing technology in factories (Atkin *et al.*, 2017; Juhász *et al.*, 2020; Macher *et al.*, 2021) or hybrid seeds (Griliches, 1957; Munshi, 2004; Suri, 2011) or use of fertilizer in farm (Duflo *et al.*, 2008; Conley & Udry, 2010). Similar phenomenon is seen in healthcare for example in adoption of telemedicine (Delana *et al.*, 2022), bed nets (Dupas, 2014), contraceptives (Munshi & Myaux, 2006), curative pills (Miguel & Kremer, 2004) or menstrual aids (Oster & Thornton, 2009). Overall, there is a large set of factors at play both on the demand and supply sides simultaneously in technology adoption.

In this paper, we study how an expensive medical technology goes through enhanced adoption by replacing existing older technology, in a setting with a not-for-profit orientation. Our context should be of interest given recent work in health economics more broadly given the welfare considerations of different business models of hospital systems predominantly from US settings (Gaynor & Vogt, 2000; Gaynor & Town, 2011; Gaynor *et al.*, 2015; Chandra *et al.*, 2016). From a cost-benefit point of view, it may appear surprising that an *expensive* technology replaces its less expensive version, seemingly without a profit motive – a theme that goes against the basic economic principle of profit incentivizing technology adoption (Acemoglu, 2002; Griliches, 1957). We demonstrate in our context that this may have happened due to supply-side push factors where younger physicians who are well versed in the new technology facilitate the replacement of the older technology preferred a priori potentially by elder physicians.

Our empirical setting leverages unique data from India where we use novel EMR data from one of the largest eyecare institutes based in Hyderabad - LV Prasad Eye Institute (LVPEI). LVPEI, a World Health Organization (WHO) approved collaborating center follows a cross-subsidization model with a not-for-profit orientation. It provides care at no cost to the economically underprivileged (henceforth named as non-paying patients) but charges from patients who can pay, adopting a cross-subsidization mechanism of later subsidizing the care of the former. The EMR data comprise patient visit-level eye diagnostics information of patients along with their demographic details. We can match physicians to every visit of a patient to the hospital. The diagnostics data provides us with the nature of patients' visual impairment and specific medical technology used for the patient. Demographic data of patients helps us analyze the demand-side heterogeneity and physician's data on age and qualification helps us develop the relevant mechanisms driving technology adoption through the supply side.

The specific technological replacement we are examining is Optical Coherence Tomography Angiography (OCTA) vis-a-vis Optical Coherence Tomography (OCT) and other scanning methods which do not use angiography. OCTA is a newer technology that produces substantially more elaborate results and information about retina than OCT owing to the implementation of angiography. LVPEI physicians had access to both types of the machines. The sample period for our data is from October 2019 to December 2020 (see figure 1), which includes a period of COVID-19 induced lockdown in India from April 2020 that offers an exogenous shock in the form of movement restrictions – especially for non-paying poorer patients who often have to travel far from villages to the city to access the hospitals – for our identification strategy.[1] We consider the category of non-paying patients as our treatment group and categories of paying patients as our control group (payments may differ based on the willingness of patients; we will explain this in more details in section 2.1). The reason for choosing non-paying category as the treated group is as follows. The

[1]We exploit additional data from the period of October 2017 to December 2018 for additional robustness checks.

pandemic caused disproportionate impact on the vulnerable population (Ceballos *et al.*, 2020; Miguel & Mobarak, 2021; Rönkkö *et al.*, 2022). Since non-paying patients who were typically low-income households who could not afford to visit the physicians as per their needs, suffered comparatively more than the paying patients leading to comparatively worse visual acuity. This relative worsening necessitates more elaborate treatment which in turn generates a demand-pull. We posit that this mechanism provides an opportunity to replace older technology. Using a difference-in-differences design, we have subsequently four sets of findings.

First, we find that when non-paying patients visited the hospital after the strict lockdown in India, they had significantly higher baseline visual impairment (or equivalently, reduced visual acuity) than the paying cohort, on average. The reason for this increase in visual impairment could be financial and also restrictions in movements during COVID-19 lockdown combined with procrastinating behavior of non-paying patients considering eye-care as non-emergency care.

Second, this increase in visual impairment triggered a demand-side pull at the hospital, resulting in increased adoption of advanced technology (OCTA) for non-paying patients (OCTA machines are technologically more sophisticated than other prevailing options like OCT among others; we provide more details in section 2.2). Compared to a similar but less advanced existing technology (OCT), we find a 21.6% points increase in adoption of OCTA for non-paying patients post-pandemic.

Third, we investigate mechanisms that facilitate this technology adoption. We find that the risk of contracting COVID-19 and subsequent complexities arriving out of it for older people ensured that young physicians (or ophthalmologists with age less than 50) were more available in the hospitals. Additionally, from empirical and anecdotal evidence, we find that the adoption of OCTA decreased with the increase in physicians' age. Combining these two, we infer that the increased presence of young physicians post-lockdown and higher adoption of advanced technology by younger physicians were likely channels that enabled a technology-push in our empirical context. This is in line with the sparse literature on demand management in healthcare that suggests how hospitals leverage their scarce resources for optimal use in response to variations in patient demand (Jack & Powers, 2004, 2009; Bjarnadottir *et al.*, 2018).

Fourth, the adoption of OCTA turns out ultimately to be beneficial for non-paying patients. In triple difference estimates, we find that post-pandemic eyesight of non-paying patients significantly improves from the first visit to last visit after using OCTA, pointing to potential welfare gains from technology adoption in our setup. Thus, we infer that organizations can direct technology adoption to match the increased demand, even in settings with a social (rather than a for-profit) motive and can generate welfare.

We conduct multiple robustness and placebo tests to ensure the validity of our results. First, after matching the treatment and control group based on covariates using coarsened exact matching, we find that all our estimates improve in magnitude and significance. Second, our findings are robust to an alternate control group comprising general paying patients (rather than all paying patients taken together as control) who are much closer in demographics to non-paying patients in our treatment group. Third, we tested also for a placebo treatment before the actual treatment by keeping the month-on-month variation the same but changing the year of treatment to two years before COVID-19. We find that all estimates come out to be insignificant in this placebo test and overall add strength to our identification strategy.

Our study contributes to the literature in primarily three ways. First, we draw attention to the literature on technological change as we explore that the direction of technology adoption in our case is not being driven by necessarily profit incentives. This is not obvious as there is enough evidence on the other extreme showing hospitals using different mechanisms to generate more and more profit (Oh *et al.*, 2018; Adelino *et al.*, 2021; Freeman *et al.*, 2017; Kuntz *et al.*, 2015). Second, our findings extend prior work on determinants of technology adoption in healthcare (Denis *et al.*, 2002; Oh *et al.*, 2005; Bonair & Persson, 1996; Roback *et al.*, 2007) by showing how the ecosystem of LVPEI and heterogeneous actors (physicians in our case) played an influencing role in the adoption of expensive technology for the needy. Third, we also advance the technology-push and demand-pull literature and further prior work herein (Arthur, 2007; Di Stefano *et al.*, 2012; Nemet, 2009) by showing that both technology-push and demand-pull play equally important roles as they interact to further innovation, especially in developing economy contexts like India.

Our work also relates to health technology diffusion broadly and particularly during pandemics as has been investigated in some recent work (Lin, 2019; Doyle *et al.*, 2019; Dosi & Soete, 2022; Adbi *et al.*, 2022) though work is sparse here from a developing world setting (Adhvaryu, 2014).

The rest of the paper is structured as follows. Section 2 discusses the institutional and healthcare technology context of our study. In section 3, we report the related literature and build our hypotheses. Section 4 outlines the data and methodology. In section 5, we present the research findings and mechanisms involved, followed by robustness checks in section 6. Finally, in section 7, we conclude and discuss managerial and policy implications of our study.

2 Context

2.1 Institutional Context – LVPEI a Not-For-Profit Eye Hospital System

LVPEI, a WHO collaborating institute since 2002, follows a three-tier eye care model that includes 176 primary vision centers that provide primary care in the districts and villages of four states in India - Telangana, Andhra Pradesh, Odisha, and Karnataka. These primary centers are linked to 18 secondary eye care centers, which are linked to LVPEI tertiary centers in cities - Hyderabad, Vijayawada, Visakhapatnam, and Bhubaneswar (Das *et al.*, 2020). LVPEI uses an economic cross-subsidy platform, wherein paying patients have a graded fee structure for the same clinical care and can avail of additional non-clinical services for a higher fee.

Underprivileged people who hold the below poverty line card issued by the government of India do not have to pay anything for the check-up and are classified as non-paying patients. Within paying category, there are three kinds of classification. The first category is named general paying; patients in this category pay the bare minimum fees of INR 350 (≈ USD 4.43).[2] The second category is named supporter; these patients are provided dedicated outpatient check-in and registration area, special waiting lounges on each floor, and special care for in-patients at a fee of INR 650 (≈ USD 8.23). The third category is of Sight-Savers; patients in this category get an air-conditioned aesthetic waiting hall, a dedicated appointment system, and lesser wait times for appointments at a fee of INR 2100 (≈ USD 26.60).

2.2 Healthcare Technology Context – OCTA

Optical Coherence Tomography (OCT) (Huang *et al.*, 1991) has been considered a major technological development in the diagnosis, treatment, and follow-up of retinal diseases (Cuenca *et al.*, 2020) in the ophthalmologic context. Owing to its high resolution and quick pace at which it informs about the retinal state, OCT provides appropriate information about retinal degeneration. Research and improvement based on OCT techniques allowed

[2] 1 USD = INR 78.95 as accessed on 3rd August 2022.

the development of OCT Angiography (OCTA) (Makita *et al.*, 2006) to visualize retinal blood vessels in patients. Building on OCT principles, OCTA provides depth-resolved images of blood flow in the retina and choroid in much larger detail as compared to the older forms of imaging (Spaide *et al.*, 2018). OCTA was introduced commercially in 2015.[3]

In comparison to other existing technologies like Fluorescein Angiography (FA) or Indocyanine Green Angiography (ICGA), OCTA is fast, non-invasive, and allows improved and accurate visualization of microvascular changes (De Carlo *et al.*, 2015). These OCTA features and others have been shown to predict disease progression (de Oliveira Dias *et al.*, 2018; Heiferman & Fawzi, 2019; Sun *et al.*, 2019). The predictive capacity of OCTA, as well as its ability to detect subclinical pathologic changes in a non-invasive way (Bailey *et al.*, 2019; Heiferman & Fawzi, 2019), makes it ideally suited for monitoring and diagnostic imaging (Hormel *et al.*, 2021). OCTA efficiently evaluates common ophthalmologic diseases such as diabetic retinopathy, artery and vein occlusions, age-related macular degeneration (AMD), and glaucoma (De Carlo *et al.*, 2015).

Since OCTA technology is concerned with detecting the state of the retina, we concentrate our study on the two most common retinal disorders, Diabetic Macular Edema (DME) and Branch Retinal Vein Occlusion (BRVO) (Jaulim *et al.*, 2013). DME is amongst the prominent causes of visual impairment in patients suffering from diabetes mellitus. DME occurs mainly because of disruption of the blood-retinal barrier, which leads to increased accumulation of liquid within the intraretinal layers of the macula (Bhagat *et al.*, 2009). BRVO is essentially blockage of at least one branch of the central retinal vein, which runs through the optic nerve.[4] BRVO is the most common among the three types of retinal vein occlusions (Jaulim *et al.*, 2013) and is more common in patients with diabetes, high blood pressure, and atherosclerosis.

Apart from being the most common retinal disorders, these are the two most prevalent diseases for which OCTA/OCT technology is used in LVPEI. It is useful here to also remember that India is well acknowledged as the diabetes capital of the world. Thus, there is a broader health policy implication of our study, given that retina disorders resulting from diabetes and allocative conversations about health technology are at the center of universal health coverage debates given the rising burden of diabetic retinopathy in India (Burton *et al.*, 2021). Optimal delivery models explored here globally apply in terms of health system lessons not just in India but many other related economies like Brazil, Indonesia,

[3] https://www.laserfocusworld.com/biooptics/bioimaging/optical-coherence-tomography/article/14191316/zeiss-receives-fda-approval-for-oct-angiography-technology

[4] https://www.willseye.org/branch-retinal-vein-occlusion-brvo

Bangladesh or South Africa.

3 Theoretical Background and Hypotheses

In this section, we integrate relevant insights from previous research to develop our hypotheses regarding how technology got adopted and replaced older technology for non-paying patients, eventually improving their health outcomes.

The Government of India imposed one of the strictest lockdown globally to prevent the spread of COVID-19 starting 24th March 2020.[5] COVID-19-induced lockdown impacted the demographic and clinical presentation of patients with ocular disorders in India (Das & Narayanan, 2020). There is recent literature on how COVID-19 caused disproportionate impact on the vulnerable population in developing countries (Miguel & Mobarak, 2021; Rönkkö *et al.*, 2022; Ceballos *et al.*, 2020; Kansiime *et al.*, 2021). In terms of impact on eye care, it has been studied that restricted movement during lockdown meant many could not go out for eye check-ups. People with irregular incomes (non-paying patients in our case) were busy fulfilling basic necessities potentially keeping eye-care on low priority. This delay or suspension in eye-care caused significant and rapid vision impairment to irreversible blindness to many (Toro *et al.*, 2021) and particularly to those belonging to the less privileged and poor.This leads to our first hypothesis:

Hypothesis 1 *Visual acuity of non-paying patients, worsened compared to paying patients when measured on their first visit to the hospital post COVID-19 lockdown announcement.*

Does this sudden change in visual impairment cause a demand-pull inducing technological replacement at LVPEI? Many believe that beneficial innovation will sell itself, and obvious benefits of the creative idea will be realized by the users and cause innovation to diffuse quickly. However, that's not always the case. Most innovation, in fact diffuse at an unimaginably slow rate (Rogers *et al.*, 2014). Comin & Hobijn (2010) reveal that, on average, countries took 45 years to adopt technology after their invention and recent work here also shows the role of overconfidence and perception biases causing frictions (Comin *et al.*, 2022).

This slow adoption is puzzling because new technology can significantly boost the productivity of a firm (Juhász *et al.*, 2020; Giorcelli, 2019; Bloom *et al.*, 2013; Syverson, 2011). As per Atkin *et al.* (2017), an important reason for the lack of adoption is a

[5] https://covidtracker.bsg.ox.ac.uk/stringency-scatter

misalignment of incentives within firms, given the important role of complementary assets and influencers (Adhvaryu, 2014; Teece, 1986). There are two forces affecting equilibrium levels of technology diffusion: the price effect and the market size effect. Acemoglu (2002) argues that the price effect encourages innovations directed at factors that are in short supply; on the contrary, the market size effect leads to technical change preferring factors rich in supply (Acemoglu & Linn, 2004).

More generally, there is an active literature on technology adoption in agriculture, where technology use measures are more readily available (Foster & Rosenzweig, 2010; Munshi, 2004; Bandiera & Rasul, 2006; Conley & Udry, 2010; Duflo *et al.*, 2008; Suri, 2011; Beaman *et al.*, 2014; Emerick *et al.*, 2016). On the contrary, adopting health technology is a complex process (Silva & Viana, 2011). For example, it is difficult to originate an economic model explaining decades of lag in the usage of X-rays for fractures in the early twentieth century (Howell & Harden, 1995) or why it took more than a century for the British Navy to mandate the use of lemons in the sailors' diets when they were aware that limes prevented scurvy (Berwick, 2003).

Three sets of determinants play a crucial role in technology adoption in health care - characteristics of the technology, actors in the process, and structure of the environment. (Davis, 1989; Cutler & McClellan, 1996; Denis *et al.*, 2002; Rogers, 2002; Oh *et al.*, 2005; Bonair & Persson, 1996; Roback *et al.*, 2007). In healthcare technology, adoption lies as a trade-off between exploitation and experimentation which depends on the physicians' diagnostic skill (Currie & MacLeod, 2020). Physicians who reported high social participation in the medical community adopted earlier (Skinner & Staiger, 2009; Coleman *et al.*, 1957).

Most research on innovations in health care is focused on individual physicians; less is known about the determinants of innovations in larger health care organizations (Fleuren *et al.*, 2004; Gaynor & Vogt, 2000). Few prominent studies that focus on hospitals and technology adoption are, e.g., by Skinner & Staiger (2015) who find that hospitals rapidly adopting cost-effective innovations had substantially better outcomes for their patients. Lin *et al.* (2021) & Gaynor & Town (2011) examined the relationship between hospital market competition and the diffusion of health technologies, relatedly some also explore the role of organizational ownership herein (Gaynor & Vogt, 2003).

Building upon this existing literature, our work specifically highlights how advanced technology in a large-scale not-for-profit oriented eye hospital replaces the older technology due to a demand shock. Therefore, we propose the following hypothesis:

Hypothesis 2 *Adoption of advanced technology (OCTA) increased for the non-paying* *patients compared to paying patients post COVID-19 lockdown announcement – mainly to attend to the former group's worse-off visual impairment.*

Sometimes diffusion does not occur either because health professionals do not adopt the innovation or because of insufficiency in financial resources made available to implement the innovation (Fleuren *et al.*, 2004). A debate emerged in the 1960s and 1970s about whether the rate and direction of technological change have been more heavily influenced by changes in market demand (demand-pull) or by advances in science and technology (technology-push) (Nemet, 2009).

Proponents of technology-push point to the role that science and technology play in developing technological innovations and adapting to the changing attributes of the industry structure (Di Stefano *et al.*, 2012; Dosi, 1982; Bush *et al.*, 1945). Demand-pull, on the contrary, points to changes in market conditions that create opportunities for firms to invest in innovation to satisfy unmet needs (Nemet, 2009; Griliches, 1957; Schmookler, 1962, 2013; Von Hippel, 1976; Opar, 2008). The debate eventually reached a sort of stalemate in the eighties (Di Stefano *et al.*, 2012). Mowery & Rosenberg (1979) in their critique came forth to state that both demand and supply-side influences are crucial to understanding the innovation process. A clearer balance between demand-pull and technology-push has seemingly now been reached from both an empirical as well as a more micro standpoint (Di Stefano *et al.*, 2012; Pavitt, 1984). Arthur (2007) went further to state that it is not only a fact that both factors contribute, but they also interact.

We wish to empirically test the setting to understand the joint effect of demand-pull and technology-push. In Hypothesis 1 & 2, we have already conjectured how the increase in visual impairment for non-paying patients may have created a demand-pull for technology adoption and replacement. To understand the mechanism of technology-push that followed we examine the pivotal role of younger physicians during the pandemic-induced lockdown in India to facilitate technology replacement; we document the role of complementary agents reminiscent of prior work in innovation (Teece, 1986). This leads to our third hypothesis:

Hypothesis 3 *The higher presence of young physicians during the COVID-19 lockdown in hospital sites led to higher degree of utilization of OCTA.*

After establishing the role of technology-push and demand-pull in adopting technology, a final question remains unanswered. Was the adoption and replacement of older technology with newer one (OCTA) welfare enhancing?

There is a wide literature that evaluates benefits to users from new technology and the studies cover a wide range of product markets including automobiles (Petrin, 2002; Fershtman & Gandal, 1998), cellular phones (Hausman, 1999), computers (Bresnahan, 1986), cement (Macher *et al.*, 2021), hybrid seeds (Griliches, 1957; Munshi, 2004; Suri, 2011), telecommunications services (Hausman *et al.*, 1997) and fertilizers (Duflo *et al.*, 2008; Conley & Udry, 2010).

In healthcare, the classic work in the adoption of medical technology is by Trajtenberg (1989) who estimated social gains from the adoption of CT scanners. More recent work also finds how technology attenuates racial biases in healthcare delivery (Ganju *et al.*, 2020). There are also extant studies showing how technology adoption in healthcare was beneficial for e.g. adoption of telemedicine (Delana *et al.*, 2022), menstrual aids (Oster & Thornton, 2009), bed nets (Dupas, 2014), curative pills (Miguel & Kremer, 2004) or contraceptives (Munshi & Myaux, 2006).

We contribute to the existing literature by understanding how in our non-profit organization, adopting new technology to replace the older one benefited non-paying patients who otherwise may not have been able to afford its cost. This leads to our last hypothesis:

Hypothesis 4 *Adopting OCTA over existing technologies (OCT and others) post COVID-19 lockdown announcement resulted in higher visual acuity for non-paying patients in comparison to the paying patients.*

A broad pictorial representation of our study building on the above hypotheses is shown in figure 2. This figure summarizes all hypotheses (H1 to H4) along with the flow of research. In the next sections, we will evaluate these hypotheses empirically.

4 Data & Empirical Strategy

4.1 Data and Variables

Our patient data was retrieved using the information captured through the EMR system eyeSmart across the three-tier eye care network of LVPEI. The study was approved by LVPEI's IRB with the reference number LEC-BHR-R-09-20-507. A standardized consent form was filled out by the patient or their parents/guardians at the time of registration for electronic data privacy.

We specifically focus on the retina department of LVPEI, where OCTA technology is conspicuously used. Our focus is on two major diseases, Diabetic Macular Edema (DME) and Branch Retinal Vein Occlusion (BRVO), for which OCTA is prominently used.

Our baseline sample from EMR[6] comprises 2316 visits of 1076 patients attended by 47 physicians pre and post COVID-19 lockdown announcement in India. As shown in figure 1, we use data from October 2019 to December 2020, with April 2020 as the cutoff month just when the COVID-19-induced lockdown started in India.[7] We have visit level data on patient category, age, gender, home location, technology used during the visit, attending physician's name, and patient visual impairment in his/her first and last visits. Physician-specific data obtained from LVPEI comprises physicians' age and qualifications. Using the attending physician's name available in visit level data we merged information on physician's age and qualification.

To analyze the factors responsible for technology adoption, we generate three response variables. First, demand-side changes are captured through a response variable generated using the visual impairment of the patient diagnosed in the first visit. We convert the Best Corrected Visual Acuity (BCVA) noted by physicians into a standardized LogMAR scale for our analysis.[8] Second, to identify the adoption of technology, we generate an indicator variable to capture if OCTA was used in a visit compared to older available technology. Third, to measure the health outcome we obtain the difference in visual impairment in the first and last visit using LogMAR scale. Finally, we also generate another indicator variable to identify non-paying category of patients. Descriptions of all variables are provided in table 1. Summary statistics of the variables are presented in table 2.

As we follow a difference-in-differences approach, we show separate mean values for the treatment and control group pre- and post-the-shock. We can see in table 2 that for non-paying patients (Treated Group), there is an increase in visual impairment post-pandemic (1.044 to 1.159); on the contrary, there is a decrease in visual impairment for paying patients (0.842 to 0.757). This indicates that the eyesight of the non-paying category was more affected due to lockdown as compared to the paying cohort. A similar pattern is visible in the mean values of OCTA usage, where it increases for non-paying patients (0.065 to 0.087) and decreases for paying patients (0.107 to 0.073). This shows higher likelihood of adoption of OCTA for non-paying people post-pandemic. We also see a decrease in change

[6]The use of EMRs in health economics has been pointed out by a large body of extant literature – Rodriguez Llorian & Mason (2021); Dranove *et al.* (2015); Lin (2019); Susan & Stern (2002); Miller & Tucker (2011); Lee *et al.* (2013); Hydari *et al.* (2019); Angst *et al.* (2010); Ransbotham *et al.* (2021); Bhargava & Mishra (2014); Miller & Tucker (2009); Atasoy *et al.* (2021).

[7]We also do a placebo test for the period October 2017 to December 2018.

[8]The logMar scale was developed by National Vision Research Institute of Australia in 1976 and it is accepted worldwide among the opthalmologic community. See https://www.nidek-intl.com/visual_acuity.html for a mapping between visual acuity measured by distance and the logMAR scale.

in visual impairment for non-paying patients post-pandemic (-0.124 to -0.265) indicating improvement in vision.[9]

Overall, a comparison of the mean values shown in summary statistics aligns with our hypotheses that OCTA usage replacing older technologies is facilitated by an exogenous shock and generates welfare for non-paying patients. These summary statistics are of course non-parametric not controlling for several other sources of observed and unobserved heterogeneity. To account for this, we turn to a systematic regression analysis building on difference-in-differences design presented below.

4.2 Specification for Examining Visual Impairment (H1)

We begin our analysis by evaluating Hypothesis 1. We estimate the average treatment effect of the pandemic on the visual impairment of the non-paying category compared with the paying patients. We follow the below-mentioned difference-in-differences (DID) specification

$$\begin{aligned}\mathbf{Visual\_Impairment_p} = &G(\beta_0 + \beta_1\mathbf{NonPaying_p} + \beta_2\mathbf{Covid_t} \\ &+ \beta_3\mathbf{NonPaying_p} \times \mathbf{Covid_t} + \theta_p + \delta_t + \epsilon)\end{aligned} \tag{1}$$

In this analysis, we observe a pooled cross-section of individual patients p in a month t. The outcome of interest is visual impairment measured on the patient's first visit to the hospital. Given the ordered nature of the dependent variable, we use the ordered logistic function $G(.)$ for our estimation approach. The main coefficient of interest is β_3. It estimates the post- minus pre-pandemic visual impairment of the treated group (non-paying patients) relative to the control group (paying patients). We add variables for patient's age, gender, and location in the regression equation to control for patient-specific heterogeneity, represented by θ_p. We also control for month-specific unobserved heterogeneity through month dummies (δ_t). We report robust standard errors clustered at patient level.

By comparing the post- versus pre-pandemic change in visual impairment in the treated group relative to the control group, the DID approach provides causal estimates based on the "parallel trends" assumption, which implies that in the absence of the shock, outcomes for the non-paying and paying patients groups would have followed parallel trajectories over time. To establish the parallel trend assumption, we check for the existence of pre-trends

[9] Although there is a decrease in visual impairment for paying patients, the magnitude of change is comparatively small.

following (Angrist & Pischke, 2008). The below-mentioned model is used to estimate the interaction coefficient using an event study design.

$$\begin{aligned}\mathbf{Visual\_Impairment_p} =& G(\beta_0 + \beta_1 \mathbf{NonPaying_p} + \beta_2 \mathbf{Month_t} \\ &+ \sum \beta_t (\mathbf{NonPaying_p} \times \mathbf{Month_t}) + \theta_p + \delta_t + \epsilon)\end{aligned} \tag{2}$$

$Month_t$ varies from November, 2019 to December, 2020 (October, 2019, the first time point, is taken as the base).

4.3 Specification to Examine the Adoption of OCTA (H2 & H3)

Next, we use the following fixed effects specification on panel data to estimate the adoption of OCTA for non-paying patients as mentioned in Hypothesis 2 and Hypothesis 3:

$$\begin{aligned}\mathbf{OCTA_{pt}} =& \beta_0 + \beta_1 \mathbf{NonPaying_p} + \beta_2 \mathbf{Covid_t} \\ &+ \beta_3 \mathbf{NonPaying_p} \times \mathbf{Covid_t} + \theta_p + \delta_t + \gamma_d + \epsilon_{pt}\end{aligned} \tag{3}$$

The unit of analysis is patient-time, with the unit of observation being patient p administered in month t. The outcome of interest is the likelihood of adoption of OCTA. The main coefficient of interest is β_3, i.e., the coefficient of the interaction term NonPaying×Covid. It estimates the post-minus pre-pandemic change in the adoption of OCTA in the treated group (non-paying patients) relative to the control group (paying patients). We control for time-invariant patient-specific and month-specific heterogeneity by including patient fixed effects (θ_p) and month fixed effects (δ_t) in regression analysis. Since the decision to use a technology lies majorly with physicians, we add a physician dummy variable (γ_d) that controls for physician-specific variations. We use the logit model and ordinary least squares (OLS) method to estimate the coefficients and report robust standard errors clustered at the patient level.

To check for the existence of pre-trends in OCTA adoption, we use the below-mentioned equation to generate interaction coefficients using an event-study design.

$$\begin{aligned}\mathbf{OCTA_{pt}} =& \beta_0 + \beta_1 \mathbf{NonPaying_p} + \beta_2 \mathbf{Month_t} \\ &+ \sum \beta_t (\mathbf{NonPaying_p} \times \mathbf{Month_t}) + \theta_p + \delta_t + \gamma_d + \epsilon_{pt}\end{aligned} \tag{4}$$

$Month_t$ varies from November, 2019 to December, 2020 (October, 2019, the first time point, is taken as the base).

4.4 Specification to Evaluate Vision Outcome (H4)

To analyze the vision outcome of non-paying after they were treated with OCTA in Hypothesis 4, we employ a triple difference specification as shown below:

$$\begin{aligned}\mathbf{ChangeInVisualImpairment_p} =& G(\beta_0 + \beta_1 \mathbf{NonPaying_p} \times \mathbf{OCTA} \times \mathbf{Covid_t} \\ &+ \beta_2 \mathbf{NonPaying_p} \times \mathbf{OCTA} + \beta_3 \mathbf{NonPaying_p} \times \mathbf{Covid_t} \\ &+ \beta_4 \mathbf{OCTA} \times \mathbf{Covid_t} + \beta_5 \mathbf{NonPaying_p} + \beta_6 \mathbf{OCTA} \\ &+ \beta_7 \mathbf{Covid_t} + \theta_p + \delta_t + \gamma_d + \epsilon)\end{aligned} \tag{5}$$

We analyze a pooled cross-section of individual patients p in a month t. The outcome of interest is Change in Visual Impairment of a patient from the first to the last visit. Similar to equation 1, $G(.)$ is an ordered logistic function. The main coefficient of interest is β_1 i.e., the coefficient of the interaction term $NonPaying \times OCTA \times Covid$. It estimates change in visual impairment of non-paying patients for whom OCTA was applied post-pandemic lockdown in India. We add variables for patient's age, gender, and location in the regression equation to control for patient-specific heterogeneity, represented in equation 5 by θ_p. We also control for time-invariant month-specific heterogeneity through month dummies (δ_m). Since we are interested in changes in visual impairment after OCTA application and the decision to use a technology lies majorly with physicians, we add a physician dummy variable that controls for physician-specific variations. We report robust standard errors clustered at patient level.

5 Empirical Findings

5.1 Impact of COVID-19 on Visual Impairment of Non-Paying Patients (H1)

Table 3 presents the results of the regression analyses to test Hypothesis 1 by estimating equation 1. Column (1) shows the baseline estimation without any controls. In column

(2), we introduce patient-level controls like age, gender, and location in which the patient lives. In column (3), along with patient controls, we add a month dummy to account for month-specific unobserved heterogeneity.

Results in table 3 show how the pandemic worsened the visual acuity of non-paying patients. Findings in column (1) - column (3) reveal that the coefficient of the interaction term $NonPaying \times Covid$ is positive and significant ($\beta = 0.564$ in column (3)) indicating the increase in visual impairment post COVID-19 induced lockdown. The difference-in-differences generated causal estimate keeps all the three paying categories (General Paying, Supporter, and Sight-Saver) as the control group.[10] With all controls in column (3), we find that odds of non-paying patients being in a higher visual impairment scale (as per LogMAR) increases by 56.4% post-pandemic as compared to paying patients holding the other variables in the model constant.

In column (1) of table 4, we show interaction coefficients using equation 2. We look for insignificant coefficients in the pre-shock period from November 2019 to March 2020 to signify the absence of pre-trends. We find no significant difference in the non-paying (treatment) and paying (control) group till March 2020. The shift in the estimated coefficient from May 2020 onward is quite evident.[11] Thus, indicating the increase in visual impairment for non-paying patients post-pandemic induced lockdown in India.

5.2 Adoption of OCTA for Non-Paying Patients Post-Lockdown (H2)

Table 5 reports the results testing Hypothesis 2 using equation 3. We do a two-level analysis of the adoption of OCTA technology. First, in column (1) - column (3), we compare OCTA with all other technologies. Second, in column (4) - column (6) we do a more conservative analysis comparing OCTA only with OCT, the technology over which the OCTA brought advancements. Also, since the dependent variable is binary, we use the panel logit model in column (1) and column (4).[12] In all other columns we apply ordinary least square method. Robust errors are clustered at patient level in all columns.

Results in table 5 estimate change in the likelihood of adoption of advanced technology OCTA post-pandemic. We would refer to column (3) and column (6) for interpretation as

[10] In robustness check in section 6.2, we show that results hold if we keep only general paying as a control group.

[11] Interaction coefficient for April is dropped because of very few observations due to mobility restrictions caused by the lockdown.

[12] We use XTLOGIT command in STATA.

these models are most conservative with full controls and patient and month fixed effects. Column (3), where we compare OCTA with all other technologies, shows a positive and significant interaction coefficient ($\beta = 0.097$), indicating that the pandemic caused an increase in likelihood of adoption of OCTA for non-paying patients as compared to paying patients. Similarly, findings in column (6), where we compare OCTA with OCT, also indicate a positive and significant interaction coefficient ($\beta = 0.216$). Thus, adoption of OCTA technology increased by 21.6% points over OCT for non-paying patients post-pandemic compared to paying patients.

In column (2) of table 4, we show interaction coefficients using equation 4. We look for insignificant coefficients in the pre-treatment period from November, 2019 to March 2020 to signify the absence of pre-trends. We find that except for December 2019, there is no significant difference in the non-paying (treatment) and paying (control) group till March, 2020. We can see the shift in the estimated coefficient after the strict lockdown starts opening from June 2020. Thus, indicating the increase in adoption of OCTA for non-paying patients post-pandemic.

5.3 Mechanism - Physician Heterogeneity (H3)

We have found that higher visual impairment was diagnosed amongst non-paying patients after COVID-19, followed by the adoption of advanced technology for these patients. In this section, we explore the mechanisms catalyzing this technology adoption process and discuss findings related to Hypothesis 3. Since the mechanisms are related to physician-level heterogeneity, it is important to understand the different types of patient-physician decision-making models.

Prior work seems to suggest that there are four models of patient-physician decision-making in vogue - paternalistic decision-making, interpretative decision-making, shared decision-making and informed decision-making (Wirtz *et al.*, 2006). In the paternalistic model, the physician chooses the treatment after assessing information about the disease of the patient, the treatment options, and the likelihood of outcomes. In the interpretative model (Emanuel & Emanuel, 1992), the physician decides about a treatment plan but takes the preferences of the patient into consideration. Shared decision-making refers to the involvement of both physicians and patients where both parties take steps to participate in the process of treatment decision-making (Charles *et al.*, 1997). Finally, in the informed decision-making model patients decide on their own after the physician reveals benefits, risks, and alternative treatment options.

The non-paying patients are more likely to be guided by a paternalistic decision-making approach because of the following reasons. Non-paying patients, because of poor economic conditions and unavailability of information and knowledge resources, are more likely to be dependent on physicians to decide for them. Moreover, since OCTA is an advanced technology, it would be difficult even for the knowledgeable patients to get involved in decision-making. Thus, most decision-making about using OCTA would be likely driven by physicians and hence follow a paternalistic approach. Given this high involvement of the physicians in the decision-making, we study the heterogeneity of physicians based on age and qualification (See Iversen & Ma (2022)). Figure 3 shows the distribution of 47 physicians in our sample by age. Nine physicians are over the age of 50. Due to comorbidities involved, old age people were at higher risk during the COVID-19 pandemic (Lebrasseur *et al.*, 2021). For our analysis we consider physicians below age 50 to be young physicians and greater than or equal to 50 to be old.

We evaluate our Hypothesis 3 and analyze the differential adoption of OCTA by young and old physicians in table 6. In all specifications, we apply patient and month-fixed effects and show robust standard errors clustered at the patient level. Column (1) indicates that the likelihood of adoption of OCTA decreases as the age of physician increases. Column (2) - column (4) are sub-sample analysis using equation 3. In column (2), we see that for a sample of young physicians with age less than 50, the probability of applying OCTA for a non-paying patient is 8.8% points higher after COVID-19 than for paying patients. An insignificant coefficient in column (3) for old physicians justifies that the adoption of OCTA was driven by young physicians.

In another analysis, we divide physicians in our sample based on five different qualifications they possess in Ophthalmology (See figure 4). From the pie chart, 23% of physicians hold either a Diploma in National Board (DNB) or a super specialty degree (Fellow) in India. We consider physicians with DNB or Fellow degrees to be holding higher qualifications. We check if qualification holds a bearing in physician decision-making in table 7 and find support. In all specifications, we apply patient and month-fixed effects.

Column (1) indicates that, in general, the likelihood of adoption of OCTA decreases with increasing qualification. This is in sync with table 6 as generally, qualification increases with age. Column (2) and column (3) are sub-sample analyses done using equation 3. In column (2), we see the probability of OCTA adoption for non-paying patients by physicians with basic qualifications[13] increases by 10.9% points post-pandemic. In column (3), the

[13]Diploma in Ophthalmic Medicine & Surgery (DOMS) or Master of Surgery (MS)

interaction coefficient becomes indifferent for physicians with high qualifications.

Overall, we unearth two basic findings while unpacking heterogeneity conditional on a paternalistic approach. First, since OCTA is relatively modern technology, old physicians are probably not aware or reluctant to apply it to patients (Iversen & Ma, 2022). Second, the health risks involved during COVID-19 meant older physicians were less available to see the patients. Thus, as young physicians are more prone to use OCTA for patients with DME or BRVO disease and because they are also more available in the hospital, we see an increase in adoption of expensive yet advanced technology for patients in higher need.

We also interviewed physicians to check consistency of these findings with their experiences. A common statement made by all physicians interviewed, irrespective of age, was – "*physicians at LVPEI don't differentiate between paying and non-paying patients*". A young physician mentioned – "*adoption of OCTA can bring better health outcomes for patients with retinal disorders*". Another young physician said – "*I would always use OCTA for a BRVO patient. Though it takes more time than OCT, the outcome with OCTA is more comprehensive.*" In contrast to these views old physicians wished to stick with older technologies like OCT. In our talk with the older physicians, one of them mentioned that – "*since OCTA is a time-taking procedure, I generally prefer to stick to OCT as it covers most of the issues for DME patients*". Overall, our interactions with physicians reinforces our empirical findings that hint a penchant of young physicians to use advanced technologies like OCTA and thus provide strength to the mechanism that presence of young physicians acted as catalyst in adoption of OCTA.

5.4 Improvement in the Vision of Non-Paying Patients after OCTA Use (H4)

In table 8 we estimate Hypothesis 4 using equation 5. In this triple difference estimate, we analyze how the visual acuity of the non-paying patients improved with the adoption of OCTA after COVID-19. Like table 5, we do a two-level analysis. In columns (1) and (2), we take the full sample and compare the adoption of OCTA with all other technologies. Secondly, we do a subsample analysis in columns (3) and (4) to identify the effect on change in impairment after adopting OCTA compared with OCT. In all models we control for patient age, gender and district location. We also control for physician and time heterogeneity using physician and month dummy.

We use columns (2) and (4) for interpretation as we apply all controls in these models. Triple interaction coefficient of $NonPaying \times OCTA \times Covid$ in column (2) is negative and significant (β = -1.361). In a more specific estimate where we compare OCTA with OCT in column (4), we find the same coefficient negative and significant (β = -2.524). Thus, the odds of being in a higher visual impairment scale (as per logMAR) would decrease by 252% for non-paying patients treated with OCTA post-pandemic. The results, therefore, indicate that along with the increase in technology adoption and replacement of OCT with OCTA driven by demand-pull and technology-push facilitated by young physicians, the net effect was potentially welfare-enhancing improving the health outcome of the patients most in need.

6 Robustness

6.1 Coarsened Exact Matching (CEM)

In all our specifications till now, the treatment group comprises non-paying patients and the control group chosen are the patients in paying category. A systematic difference in the income levels of the two groups can be a cause of concern which may cause bias in the estimation. To mitigate this concern, we use coarsened Exact Matching, CEM in short (Iacus *et al.*, 2012). CEM is a method for estimating causal effects by bringing down imbalance in covariates between treated and control groups (Blackwell *et al.*, 2009). In reducing the imbalance, CEM generates matching weights which are then used in the regression. Few observations drop out from the estimation as they receive zero weight owing to the unavailability of proper match.

Compared to other existing matching methods, CEM possesses improved statistical properties. These advantages of the CEM method have led to frequent usage of this method in multiple recent studies (see, e.g., Wang & Zheng (2022); Fry (2021); Chen *et al.* (2022)) as a means for robustness test for difference-in-differences estimates where the choice of control groups may influence the resulting estimates. We match the treatment (non-paying patients) and control (paying patients) based on age, gender, and location of their home. Estimates generated by CEM on coarsened data are shown in table 9. Although there is a small drop in the number of observations, all the interaction coefficients (DID in columns (1) to (3) and Triple difference in columns (4) and (5)) have improved both in magnitude and significance. Thus, the results from the matching technique help in strengthening our causal inference.

6.2 Alternate Control Group

The control group in all specifications as of now has been patients in paying category. But as explained in section 2.1, within the paying category, there are three sub-identifications used in LVPEI. The general paying category that pays the bare minimum amount ideally comes closest to non-paying category patients in terms of demographic and income parameters. This motivated us to generate a specification where we keep only general paying patients as the control group and drop the observations with the other two paying categories. Estimates generated using this alternative specification are shown in table 10.

Interaction coefficient $NonPaying \times Covid$ as shown in column (1) indicates that odds of being in a higher visual impairment scale for non-paying patients increase by 57% compared to general paying patients post-pandemic. Similarly, we see that likelihood of OCTA adoption for non-paying patients as compared to General paying patients increases by 8.3% points and 20.1% points, taking all technologies and OCT as base in column (2) and column (3), respectively. Lastly, while the coefficient in column (4) is insignificant, the triple interaction coefficient in column (5) indicates that the adoption of OCTA over OCT improved the vision of non-paying patients compared to general paying patients. These results also help us establish that baseline estimation shown in table 3, table 5 and table 8 are not completely driven by extreme values of the other two types of patients (Supporters and Sight-Savers) in the control group.

6.3 Placebo Test with 2017-18 Sample

As shown in figure 1 our timeline is from October 2019 to December 2020, with the COVID-19 shock coming in April 2020. In this exercise, we replicate all our estimations with a changed timeline exactly two years before, from October 2017 to December 2018, with an alternate placebo treatment from April 2018.[14] Estimations are shown in table 11. As we can see that all interaction coefficients in all estimations are insignificant. Thus, by keeping a similar time trend month-on-month, a placebo treatment two years before doesn't cause changes. This analysis helps us establish the exogenous nature of COVID-19 shock and the effects caused by it and also helps in ruling out existing pre-trends (if any).

[14]We didn't choose a one-year before timeline from October 2018 to December 2019 for placebo test as it would have an overlap with the original timeline.

7 Discussion & Conclusion

There has been a significant surge in the usage of technology post-pandemic, especially in healthcare (Barnes, 2020; Fan *et al.*, 2022). It is thus becoming increasingly important to understand technology adoption in healthcare and the mechanisms involved therein. Some studies have catered to technology adoption driven by users and have dealt with hurdles underlying this demand-side mechanism (Dupas, 2014; Munshi & Myaux, 2006; Miguel & Kremer, 2004; Oster & Thornton, 2009). Findings suggest that even among the potential technology adopters, there can be a considerable delay between initial acquaintance and actual adoption (Berwick, 2003; Juhász *et al.*, 2020) and, ironically, often those who would benefit most are generally the last to adopt technology (Skinner & Staiger, 2009; Havens & Rogers, 1961).

Similarly, there are studies that attribute the supply side for the technology adoption i.e. physicians (Currie & MacLeod, 2020; Coleman *et al.*, 1957; Skinner & Staiger, 2009) and hospitals (Gaynor & Vogt, 2000; Lin *et al.*, 2021; Fleuren *et al.*, 2004; Skinner & Staiger, 2015). Proponents of technology-push indicate the role played by science & technology, actors, and their networks in technology diffusion. There also exists literature that promulgates the idea that for technology adoption to happen, both demand-pull and supply-push are important and should work in harmony (Di Stefano *et al.*, 2012; Pavitt, 1984; Arthur, 2007; Mowery & Rosenberg, 1979).

However, there exists a gap in understanding the role that interaction of demand-pull and technology-push play in organization-level technology adoption, especially in developing economies and whether such adoption is welfare enhancing or not.

In this paper, we address this gap using a unique organizational dataset of LVPEI, a WHO-approved, not-for-profit eye-care institute that cares for both paying and non-paying patients. COVID-19 pandemic disrupted the regular income flow for many in the non-paying cohort, which caused them to procrastinate their otherwise essential eye procedures. We find that compared to paying patients, the visual acuity of non-paying patients worsened when these patients first visited LVPEI post lockdown announcement. The severity of the visual impairment reflects the severity of the ocular disease and the need to provide immediate care.

We find that demand-pull generated because of increased visual impairment directed the technology adoption trajectory and increased the adoption of costly yet advanced technology for non-paying patients. The technology-push was mostly driven by young physicians who were comparatively more available during the pandemic and were more comfortable with the new technology. This increased technology adoption eventually led to improved visual acuity for non-paying patients. Thus, we observe that in our not-for-profit setting, timely alignment of demand-pull and technology-push helped in technology adoption and replacement of medical technology that positively impacted health outcomes of patients who otherwise could not even pay for regular eye checkups. This study, therefore, draws towards practical implications where organizations can help in mitigating the reluctance to technology adoption and administering the benefits realization.

From the service provider perspective, an important question that can be raised here is: Is it sustainable in the long run? Research has shown that hospital choices change in the wake of financial shocks (Adelino *et al.*, 2021) and increased workload (Freeman *et al.*, 2017; Kuntz *et al.*, 2015). The scale at which LVPEI works now makes it possible to serve the non-paying category with the best technology, but what if LVPEI wants to expand tomorrow? There exists literature specifically in healthcare settings discussing costs and benefits connected with serving different types of customers with different levels of service (Chan *et al.*, 2019). It may be important for LVPEI to establish boundaries while expanding as technologies like OCTA are expensive, and categorization of who will pay and how much on behalf of non-paying patients may change at larger scale. Further, there may also be variations in the complexity of ophthalmic technology even within LVPEI for other eye conditions that require careful investigation in future work.

Another point to be noted is that here we have focused on intra-organization adoption of technology. Inter-organization diffusion will presumably have different forms of friction which may inhibit the spread of the technology or at least affect the pace we observed within the focal organization. Thus characterizing additional frictions would be of interest from a policy perspective.

These are important themes that need deeper analysis, and there is much more that can be done by future researchers in this space of technology adoption in healthcare, specifically its interaction with profit-making incentives or lack thereof. Our work presents one step towards understanding the joint effect of demand- and supply-side influences.

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Figure 1: **Timeline of the Study**. The treatment group comprises non-paying patients, and the control group is all categories of paying patients. The study period is from October 2019 to December 2020. 'Covid' indicates months from April 2020 onwards.

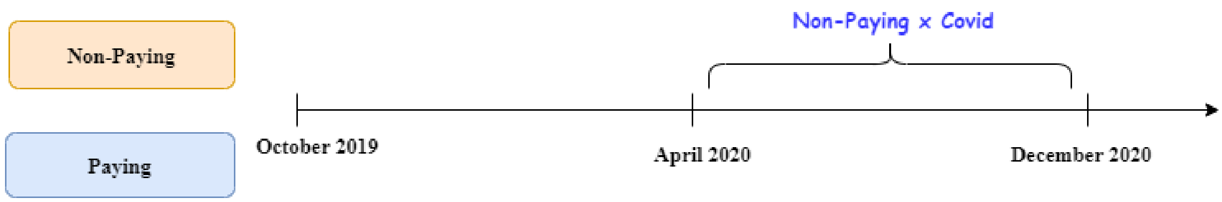

Figure 2: **Pictorial Representation of Study**. This figure shows how COVID-19 affected the cohorts of patients and physicians and the interaction that causes technology adoption. The figure, in a way also represents the flow of research. In the pictorial representation, we also indicate summary of all the hypotheses (H1 to H4).

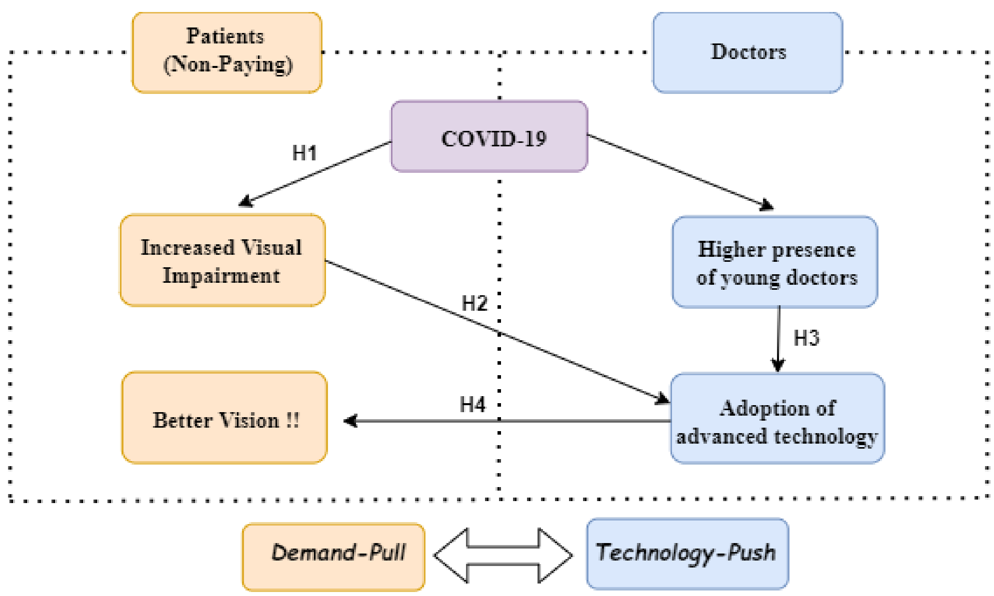

Figure 3: **Physician Heterogeneity by Age.** The y-axis shows different age brackets, and the x-axis indicates the number of physicians in that age bracket in our sample.

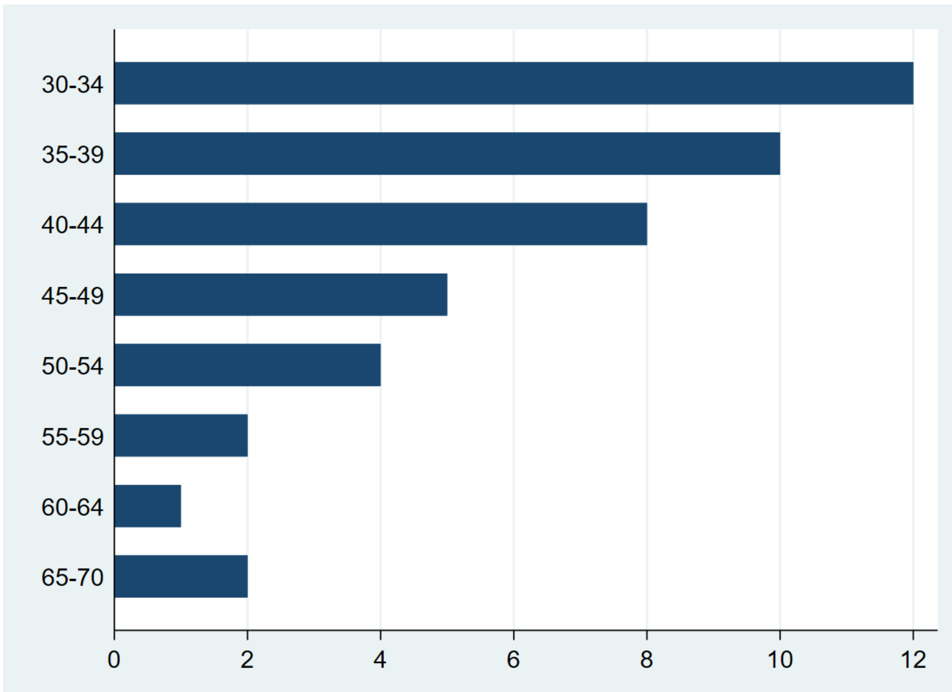

Table 1: Variable Description

Dependent Variables	**Definition and Construction**
Visual Impairment	Measured using LogMAR scale between -0.3 to 3; -0.3 refers to mild to no visual impairment and 3 refers to blindness
OCTA	Coded as 1 if the technology used for diagnosis is OCTA, 0 if any other technology is used
Change in Visual Impairment	Difference between Visual Impairment diagnosed in first and last visit
Independent Variables	**Definition and Construction**
Non-Paying	Coded as 1 if the category of patient is non-paying, 0 for other categories - general paying, supporter, and sight saver
Covid	Coded as 1 if the visit is after April 2020, 0 otherwise

Figure 4: **Physician Heterogeneity by Qualification.** Pie chart shows the distribution of physicians' qualifications in our sample. We consider DNB and Fellow to be highly qualified and physicians with DOMS and MS to have basic qualifications.

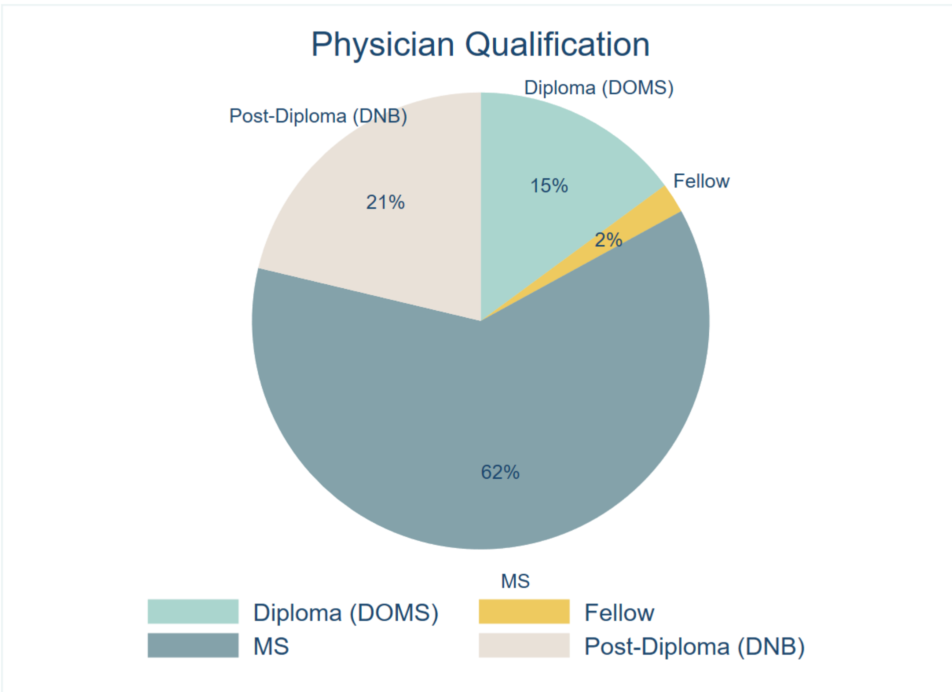

Table 2: Summary Statistics

The table shows the number of observations, mean and standard deviation separately for non-paying and paying patients from October 2019 to December 2020 – with a split at April 2020 indicating pre- and post-treatment periods.

Non-Paying				Paying			
October 2019 to March 2020	N	Mean	Std. Dev.	October 2019 to March 2020	N	Mean	Std. Dev.
Visual Impairment in First Visit	84	1.044	0.846	Visual Impairment in First Visit	652	0.842	0.761
OCTA	274	0.065	0.248	OCTA	1077	0.107	0.310
Change in Visual Impairment	87	-0.124	0.679	Change in Visual Impairment	314	-0.146	0.718
OCT	274	0.580	0.494	OCT	1077	0.465	0.499
Patient Age	274	56.565	9.517	Patient Age	1077	59.412	10.010
Female	274	0.317	0.466	Female	1077	0.364	0.481
April 2020 to December 2020	N	Mean	Std. Dev.	April 2020 to December 2020	N	Mean	Std. Dev.
Visual Impairment in First Visit	85	1.159	0.921	Visual Impairment in First Visit	571	0.757	0.761
OCTA	217	0.087	0.283	OCTA	748	0.073	0.261
Change in Visual Impairment	83	-0.265	0.740	Change in Visual Impairment	301	-0.239	0.712
OCT	217	0.483	0.500	OCT	748	0.446	0.497
Patient Age	217	54.847	10.427	Patient Age	748	56.877	9.709
Female	217	0.345	0.476	Female	748	0.332	0.471

Table 3: Change in Visual Impairment for Non-Paying Patients after COVID-19 Lockdown

DV: Visual Impairment	(1)	(2)	(3)
Non-Paying × Covid	0.484*	0.603**	0.564**
	[0.281]	[0.281]	[0.285]
Non-Paying	0.462**	0.340*	0.363*
	[0.196]	[0.200]	[0.202]
Covid	-0.262***	-0.137	-0.251*
	[0.102]	[0.103]	[0.130]
Patient Controls	No	Yes	Yes
Observations	1,392	1,392	1,392
Month Dummy	No	No	Yes

Notes: The dependent variable in all columns is Visual Impairment. Across model specifications, we see that the interaction term is positive and statistically significant. Thus, visual impairment increased significantly post COVID-19 for Non-Paying patients. The time horizon is October 2019 to December 2020. The constant term is included but not reported. Robust standard errors clustered at patient level are presented in the parenthesis.'***','**','*' indicate significance at the 1%, 5% and 10% respectively.

Table 4: Event Study Pre-Trend Analysis

	(1) Visual Impairment	(2) OCTA vs. OCT
Non-Paying × Nov 2019	-0.008	0.184
	[0.386]	[0.127]
Non-Paying × Dec 2019	0.159	0.202**
	[0.480]	[0.081]
Non-Paying × Jan 2020	0.740	0.084
	[0.450]	[0.094]
Non-Paying × Feb 2020	0.809	0.145
	[0.506]	[0.088]
Non-Paying × Mar 2020	0.298	0.124
	[0.847]	[0.102]
Non-Paying × May 2020	1.285***	0.199
	[0.495]	[0.122]
Non-Paying × Jun 2020	1.042**	0.351*
	[0.441]	[0.183]
Non-Paying × Jul 2020	-0.994*	0.259***
	[0.598]	[0.100]
Non-Paying × Aug 2020	2.012*	0.384**
	[1.046]	[0.165]
Non-Paying × Sep 2020	0.454	0.260**
	[0.551]	[0.116]
Non-Paying × Oct 2020	1.769**	0.253***
	[0.739]	[0.098]
Non-Paying × Nov 2020	1.521***	0.166**
	[0.364]	[0.082]
Non-Paying × Dec 2020	0.674	0.314**
	[0.429]	[0.153]
Patient Controls	Yes	NA
Month Dummy	Yes	NA
Physician Dummy	NA	Yes
Observations	1,392	1,307
Patient Fixed Effects	NA	Yes
Month Fixed Effects	NA	Yes

Notes: The dependent variable in column (1) is Visual Impairment, and in column (2) is OCTA. We can see that the interaction coefficients of both models are mostly insignificant before the cutoff of April 2020. The shift in the coefficients from zero to positive and significant values post-COVID19 is evident and fully consistent with the baseline difference-in-differences results. The time horizon is October 2019 to December 2020. Interaction coefficient for April is dropped because of very few observations due to mobility restrictions caused by the lockdown. The constant term is included but not reported. Robust standard errors clustered at patient level are presented in the parenthesis. '***','**','*' indicate significance at the 1%, 5% and 10% respectively.

Table 5: Change in the Likelihood of OCTA Adoption for Non-Paying after COVID-19 Lockdown

	(1)	(2)	(3)	(4)	(5)	(6)
	OCTA vs. All Other Technologies			OCTA vs. OCT		
	Logit	OLS	OLS	Logit	OLS	OLS
Non-Paying × Covid	1.078**	0.093**	0.097**	1.466**	0.202**	0.216***
	[0.537]	[0.044]	[0.045]	[0.632]	[0.079]	[0.080]
Covid	-0.569**	-0.040	-0.076**	-0.563*	-0.058	-0.103
	[0.250]	[0.032]	[0.038]	[0.293]	[0.067]	[0.075]
Non-Paying	-0.629*			-1.024**		
	[0.359]			[0.406]		
Physician Dummy	No	Yes	Yes	No	Yes	Yes
Observations	2,316	2,316	2,316	1,307	1,307	1,307
Number of Patients	1,076	1,076	1,076	747	747	747
Patient Fixed Effects	No	Yes	Yes	No	Yes	Yes
Month Fixed Effects	No	No	Yes	No	No	Yes

Notes: The dependent variable in all columns is the likelihood of adoption of OCTA. In columns (1) to (3), we compare OCTA with all other technologies, and in columns (4) to (6) we compare OCTA only with OCT. Across model specifications, we see that the interaction term is positive and statistically significant. Thus, likelihood of OCTA adoption increased significantly post COVID-19 for Non-Paying patients. The time horizon is October 2019 to December 2020. The constant term is included but not reported. Robust standard errors clustered at patient level are presented in the parenthesis. '***','**','*' indicate significance at the 1%, 5% and 10% respectively.

Table 6: Mechanism - Adoption of OCTA Technology by Young Physicians

DV: OCTA	(1) All Physicians	(2) Young Physicians (Age $<$ 50)	(3) Old Physicians (Age $\geq$ 50)
Physician's Age	-0.002*		
	[0.001]		
Non-Paying $\times$ Covid		0.088*	0.037
		[0.052]	[0.043]
Covid		-0.077*	-0.047
		[0.047]	[0.058]
Physician Dummy	No	Yes	Yes
Observations	2,316	1,924	392
Number of Patients	1,076	925	228
Patient Fixed Effects	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes

Notes: The dependent variable in all columns is the likelihood of OCTA compared with all other technologies. In column (1), we check likelihood of adoption of OCTA with increasing age of the physician. In columns (2) and (3) we do sub-sample analysis varying physician's age to be less than 50 and at least 50, respectively. The time horizon is October 2019 to December 2020. The constant term is included but not reported. Robust standard errors clustered at patient level are presented in the parenthesis. '***','**','*' indicate significance at the 1%, 5% and 10% respectively.

Table 7: Mechanism - Adoption of OCTA Technology by Physicians with Basic Qualification

DV: OCTA	(1) All Physicians	(2) Basic Qualification	(3) High Qualification
Physicians' Qualification	-0.232**		
	[0.094]		
Non-Paying × Covid		0.109**	0.051
		[0.046]	[0.075]
Covid		-0.080**	0.027
		[0.041]	[0.034]
Physician Dummy	Yes	Yes	Yes
Observations	2,316	2,177	139
Number of Patients	1,076	1,041	92
Patient Fixed Effects	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes

Notes: The dependent variable in all columns is the likelihood of OCTA compared with all other technologies. In column (1), we check likelihood of adoption of OCTA with increase in physicians' qualifications. In columns (2) and (3), we do a sub-sample analysis of varying physicians' qualifications from basic to high. The time horizon is October 2019 to December 2020. The constant term is included but not reported. Robust standard errors clustered at patient level are presented in the parenthesis.'***','**','*' indicate significance at the 1%, 5% and 10% respectively.

Table 8: Change in Visual Impairment after COVID-19 Lockdown

DV: Change in Impairment	(1) OCTA vs. All Technologies	(2)	(3) OCTA vs. OCT	(4)
Non-Paying × OCTA × Covid	-1.553**	-1.361*	-2.594**	-2.524**
	[0.791]	[0.818]	[1.134]	[1.149]
Non-Paying × Covid	-0.011	0.051	0.287	0.555
	[0.384]	[0.379]	[0.774]	[0.834]
Non-Paying × OCTA	0.149	-0.079	0.437	0.148
	[0.637]	[0.648]	[0.977]	[1.044]
OCTA × Covid	0.945***	0.922**	1.337**	1.313**
	[0.360]	[0.383]	[0.558]	[0.622]
OCTA	-0.082	-0.046	-0.365	-0.242
	[0.333]	[0.345]	[0.599]	[0.656]
Non-Paying	-0.005	-0.036	-0.272	-0.416
	[0.269]	[0.267]	[0.514]	[0.548]
Covid	-0.496***	-0.513**	-0.722*	-1.202**
	[0.167]	[0.224]	[0.390]	[0.528]
Physician Dummy	Yes	Yes	Yes	Yes
Observations	785	785	243	243
Patient Controls	Yes	Yes	Yes	Yes
Month Dummy	No	Yes	No	Yes

Notes: The dependent variable in all columns is Change in Visual Impairment. In columns (1) and (2), we compare OCTA with all other technologies, and in columns (3) and (4) we compare OCTA with only OCT. Across model specifications, we see that the interaction term is negative and statistically significant. Thus, vision improved with OCTA adoption post-COVID-19 for non-paying patients. The time horizon is October 2019 to December 2020. The constant term is included but not reported. Robust standard errors clustered at patient level are presented in the parenthesis. '***','**','*' indicate significance at the 1%, 5% and 10% respectively.

Table 9: Coarsened Exact Matching (CEM) Estimates

	(1) Visual Impairment	(2) OCTA vs All OCTA	(3) OCTA vs OCT OCTA	(4) OCTA vs All Change in VI	(5) OCTA vs OCT Change in VI
Non-Paying × Covid	0.868***	0.127**	0.306***	0.461	1.370
	[0.314]	[0.055]	[0.095]	[0.434]	[0.995]
Non-Paying × Covid × OCTA				-1.715*	-2.571**
				[0.961]	[1.270]
Non-Paying × OCTA				-0.305	-0.983
				[0.823]	[1.185]
Covid	-0.344*	-0.093*	-0.206**	-1.159***	-2.183***
	[0.184]	[0.054]	[0.099]	[0.305]	[0.695]
Non-Paying	0.132			-0.263	-0.840
	[0.231]			[0.328]	[0.698]
OCTA				0.023	0.291
				[0.514]	[0.839]
OCTA × Covid				1.424***	1.689**
				[0.541]	[0.860]
Patient Controls	Yes	No	No	Yes	Yes
Physician Dummy	No	Yes	Yes	Yes	Yes
Month Dummy	Yes	NA	NA	Yes	Yes
Observations	1,105	1,920	1,146	616	194
Patient Fixed Effects	NA	Yes	Yes	NA	NA
Month Fixed Effects	NA	Yes	Yes	NA	NA

Notes: The dependent variable in column (1) is Visual Impairment, in columns (2) and (3) is OCTA, and in columns (4) and (5) is Change in Visual Impairment. Columns (3) and (5) are sub-sample analyses where we compare the adoption of OCTA only with OCT. Across model specifications, we see that the interaction term follows the same sign and significance as baseline results. The time horizon is October 2019 to December 2020. The constant term is included but not reported. Robust standard errors clustered at patient level are presented in the parenthesis.'***','**','*' indicate significance at the 1%, 5% and 10% respectively.

Table 10: Estimates using an Alternate Control Group of General Paying Patients

	(1) Visual Impairment	(2) OCTA vs All OCTA	(3) OCTA vs OCT OCTA	(4) OCTA vs All Change in VI	(5) OCTA vs OCT Change in VI
Non-Paying × Covid	0.573**	0.083**	0.201***	0.011	0.405
	[0.286]	[0.041]	[0.071]	[0.388]	[0.865]
Non-Paying × Covid × OCTA				-1.342	-1.964*
				[0.819]	[1.133]
Non-Paying × OCTA				-0.082	-0.088
				[0.644]	[1.005]
Covid	-0.246*	-0.041	-0.060	-0.525**	-1.109*
	[0.135]	[0.032]	[0.055]	[0.243]	[0.580]
OCTA × Covid				0.957***	1.086*
				[0.365]	[0.624]
Non-Paying	0.347*			0.040	-0.254
	[0.204]			[0.271]	[0.575]
OCTA				0.012	-0.027
				[0.336]	[0.719]
Patient Controls	Yes	No	No	Yes	Yes
Physician Dummy	No	Yes	Yes	Yes	Yes
Month Dummy	Yes	NA	NA	Yes	Yes
Observations	1,295	2,059	1,140	711	219
Patient Fixed Effects	NA	Yes	Yes	NA	NA
Month Fixed Effects	NA	Yes	Yes	NA	NA

Notes: The dependent variable in column (1) is Visual Impairment, in columns (2) and (3) is OCTA, and in columns (4) and (5) is Change in Visual Impairment. Columns (3) and (5) are sub-sample analyses where we compare the adoption of OCTA only with OCT. Across model specifications, we see that the interaction term follows the same sign as baseline results. The time horizon is October 2019 to December 2020. The constant term is included but not reported. Robust standard errors clustered at patient level are presented in the parenthesis. '***','**','*' indicate significance at the 1%, 5% and 10% respectively.

Table 11: Robustness of Baseline Results with respect to Placebo Treatment Date (before the actual Treatment)

	(1) Visual Impairment	(2) OCTA vs All OCTA	(3) OCTA vs OCT OCTA	(4) OCTA vs All Change in VI	(5) OCTA vs OCT Change in VI
Non-Paying × Covid	0.203	0.034	0.079	-0.336	-1.000
	[0.219]	[0.036]	[0.058]	[0.698]	[1.368]
Non-Paying × Covid × OCTA				-0.837	-1.603
				[1.454]	[2.105]
Non-Paying × OCTA				0.217	-0.223
				[1.202]	[1.789]
Covid	0.258*	0.002	0.003	-0.458	-0.976
	[0.132]	[0.031]	[0.050]	[0.367]	[1.125]
Non-Paying	0.625***			0.275	1.179
	[0.151]			[0.541]	[0.867]
OCTA				-0.468	-0.589
				[0.495]	[1.183]
OCTA × Covid				1.504***	2.454**
				[0.546]	[1.045]
Patient Controls	Yes	No	No	Yes	Yes
Physician Dummy	No	Yes	Yes	Yes	Yes
Month Dummy	Yes	NA	NA	Yes	Yes
Observations	1,965	2,983	1,643	320	107
Patient Fixed Effects	NA	Yes	Yes	NA	NA
Month Fixed Effects	NA	Yes	Yes	NA	NA

Notes: The dependent variable in column (1) is Visual Impairment, in columns (2) and (3) is OCTA, and in columns (4) and (5) is Change in Visual Impairment. Columns (3) and (5) are sub-sample analyses where we compare the adoption of OCTA only with OCT. Across model specifications, we see that the interaction term is insignificant indicating no effect if the shock is shifted two years ago. The time horizon is October 2017 to December 2018 with a placebo shock in April 2018. The constant term is included but not reported. Robust standard errors clustered at patient level are presented in the parenthesis. '***','**','*' indicate significance at the 1%, 5% and 10% respectively.