Texting to Save Lives:
Evaluation of a Reform in Cardiovascular Treatment in Mexico

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Abstract

Can widespread technology be leveraged to reduce healthcare fragmentation in a cost-effective way? I evaluate a program implemented by the largest public healthcare provider in Mexico (IMSS) that aims to reduce heart attack mortality by minimizing time to treatment for patients. The program improves within hospital capabilities and increases across hospital transfer coordination through a group chat. I first document a large effect among hospitals that have a higher survival gap relative to the specialized centers they can send patients to: survival rates increase by 29% (11pp) and transfers by 85% (5pp). I then present a model that disentangles the capabilities and communication channels and allows me to link the reduced form results to structural parameters. Counterfactual policy analysis shows that the chat groups are responsible for 67% of the survival effect and that, without the improvements in capabilities, transfers would have been substantially higher.

1 Introduction

Radical improvements in information technology has been referred to as the "fourth industrial revolution" because of the potential to dramatically increase productivity and reshape the way we interact. Industries like transportation, home entertainment and food delivery, among many others, have experienced dramatic changes and now rely on applications that automate and optimize delivery of services.

One of the most exciting industries where this technological revolution could have positive impacts is healthcare. Healthcare delivery relies on a physician analyzing information in order to properly diagnose and treat a patient. Oftentimes, the patient's data comes from several sources and being able to see the full picture is key for a doctor make the right decision. A lack of coordination and efficient communication across providers hinders the ability to provide high quality care by leading to delays in treatment and increasing the risks of misdiagnosis and mistreatment, especially after transfers. The risk of such effects being fatal increase whenever the patient has an acute condition that requires immediate attention or is seeing several specialists for a complicated illness. Moreover, failing to coordinate is costly as it often leads to double-testing and over-prescribing.

Information and communication technology (ICT) can, in principle, solve most of the barriers to information sharing and coordination by automatizing reports and providing immediate access to a patient's medical history through electronic health records (EHR), a substantial improvement over having to go through another physicians illegible handwriting or imagining the results while talking over the phone. In a famous RAND study, (Hillestad et al., 2005) argue that, with efficient implementation, widespread EHR adoption could lead to savings of over $81 billion USD a year while improving health-care efficiency and safety. Based on its potential, several nations have stressed the use of ICT in healthcare as a mechanism to improve efficiency and clinical outcomes and have spent billions of dollars to try and achieve a centralized electronic health record with information exchange capabilities.

The U.S in one of such countries. The 2009 Health Information Technology for Economic and Clinical Health (HITECH) Act, part of the Affordable Care Act, spent around $30 billion to increase the take-up of electronic health records (EHRs) and the 21st Century Cures Act aims to regulate EHR systems to make sure that information is efficiently shared across systems. Figure 1 reports hospital EHR adoption evolution in the U.S. We can see that prior to the HITECH act adoption was under 20% and has since then increased dramatically to over 85%. Despite these large investments, however, the literature finds overall small positive effects of health information technology adoption, with vast heterogeneity, and many adopters getting no positive returns whatsoever. One main hypothesis for these results is surprisingly simple: that the systems do not communicate well across providers. A subsequent RAND study by (Kellermann and Jones, 2013) shows that the predicted effects had not materialized due, in part, to a lack of information sharing across providers.

In this paper I ask whether a low-cost intervention to leverage already widespread technology through improved communication can improve provider coordination and patient outcomes. In particular, I exploit the implementation of a policy that improved communication across hospitals in the public Mexican healthcare sector by creating chat groups between physicians at different hospitals within a network.

The Mexican public healthcare system caters to 83% of individuals in Mexico and is composed of several institutions. The largest one is the Instituto Mexicano del Seguro Social (IMSS) which services over 70 million people with 1,522 primary care clinics, 256 secondary care hospitals and 36 tertiary (high-specialty) hospitals. IMSS services are organized into regions that combine the 3 levels of service to provide care for a certain area. Unless it is an emergency, a patient is referred from the primary care clinic to the secondary hospital and in turn to the tertiary one if needed. [1]

Most care organizations rely on general physicians or hospitals treating most cases and asking specialized hospitals to help only on complicated situations. This is, in principle, efficient system design when there is significant heterogeneity across patients and many can be treated cost effectively at less specialized hospitals. But the system only works well if there is effective coordination between different levels of provision – particularly for acute conditions that require immediate transfers. Without effective communication, inefficient transfers between levels of care could result in unnecessary costs and even death.

Heart attacks are one example of such conditions. A heart attack can be treated by fibrinolytic therapy (FT) or percutaneous coronary intervention (PCI). FT consists of drugs that help the body dissolve clots and is widely available. PCI is a more complicated procedure that consists of inflating a balloon were the narrowing of the artery occurred and installing a stent that enables it to stay unblocked. The latter procedure needs to be performed by a specialist and not every hospital can do so, but allows complicated patients to survive. Transfers are key in this setting because if a patient requires PCI, every minute that passes increases the likelihood of death. Current American Heart Association Guidelines recommend getting the transferred patient to PCI in under 120 min of the first contact.

Heart attacks provide a useful setting to look for fragmentation within a system since poor coordination will lead to large differences in productivity among hospitals that have different capabilities but are close to each other. Without inefficiencies, patients who need PCI would be transferred quickly and disparities would be small. (Rathod et al., 2020) document that the difference in survival between

[1] (IMSS, 2020), (INEGI, 2017)

arriving with a heart attack to a PCI-capable hospital and others within London is under 1.5%. IMSS hospitals within Mexico City, on the other hand, are a clear example of a fragmented network as heart attack patients that arrive directly to a hospital that is capable of performing PCI have an 86 percent survival rate while patients that arrive to non-PCI capable hospitals first have only a 54 percent chance to live.

One reason for the low rate of transfer is poor communication between general hospitals and PCI-capable hospitals. In Mexico, to transfer a patient, a doctor had to call the PCI-hospital, talk to a secretary and explain the need to talk to a physician. Then wait for that person to get hold of someone and then make the argument of why such a patient needed a transfer over the phone. Moreover, after getting transferred and getting to the reperfusion center, the patient would have to be assigned to the next available physician in the urgent wing. Once assigned, the urgent wing doctor would have to read through the notes made at the general hospital for the first time and would potentially order additional tests to assess the patient's status before treatment. With (Scholz et al., 2018) estimating an increase of more than 3pp in the likelihood of dying for every additional 10 minutes it takes to transfer a patient with cardiogenic shock, this kind of fragmentation proves deadly.

In such a situation, policy makers have two options to improve outcomes: improving communication to allow for more effective transfer across hospitals, or investments in the capabilities of secondary hospitals to treat more complicated patients. In 2015, the economist running IMSS together with the cardiology head at one of Mexico City's PCI capable hospitals set up the "Código Infarto" (CI) program that aims to reduce time to treatment for heart attack patients in IMSS hospitals through both components. The first channel is surprisingly simple and cost effective: doctors in low and high specialty hospitals opened chat groups on common chat apps (mainly Whats-App) on which they shared information on patients. Building on the already existing app infrastructure, doctors are able to send ECG scans to other physicians and coordinate transfers much more quickly. In addition, there was a more sizeable investment in care at secondary hospitals: the program trained every staff member on the basic symptoms of a heart attack and prioritized a room for heart attack patients so that they would be treated sooner.

The program started in Mexico City's south network and has since expanded to the 23 networks and 191 hospitals that cover the country's heart attack treating hospitals. In each of these networks, a PCI-capable reperfusion center (RC) oversees general hospitals (GH) and can receive transferred patients from a GH that require PCI. To study the effect of CI, I use detailed case-level data for 80,354 heart attack cases containing the date of entry to the hospital, diagnosis, whether or not they were transferred and survival outcome. I label each case by the initial urgent wing they visited, so either RC or GH. A patient who was transferred from a GH to a RC will still be labelled as GH since she went there first.

I begin with a case study of the Mexico city experience, drawing on a natural control group of Northern Mexico city hospitals who were not treated by this program. I then expand the analysis to the entire nation , using the timing of implementation within networks to create a quasi-experimental evaluation framework. Because the intervention started at a different date for each network, I utilize a stacking procedure to prevent negative weighing and estimate the effect of the intervention through difference-in-difference (DID) estimations.

I find that the CI program led to a 7% (3.7pp) increase in survival rate and a 25% (2.5pp) increase in transfers, with transfers becoming 25% (2 hours) faster on average. This is an enormous improvement in survival rates, which is almost 50% bigger than the mean 2.6pp that heart attack mortality improved between 2007 and 2017 in OECD countries (O.E.C.D, 2019). Moreover, I confirm that this effect is causal by showing that the effect is driven by hospitals that have a larger survival rate gap to their reperfusion center. Hospitals in the top tercile exhibit a 29% (12pp) increase in survival and an 85% (5pp) increase in transfers. These results highlight that the intervention worked best when there was more to gain from additional transfers.

While the above results show that the intervention works, we cannot draw conclusions on mechanisms since calculating either of the program's components contribution by conditioning on transfer status would be biased by a selection effect. The within component probably reduced the need to transfer patients by increasing capabilities and the across component increased the ability to do so, probably inducing additional transfers of more complicated patients. Disentangling the contribution is key from a policy perspective as replicating the communication component of the program is straightforward in other settings with similar barriers to coordination.

In order to disentangle the contribution of each component I develop a structural model where physicians at hospitals with heterogeneous capabilities decide how to treat a heart-attack patient. In sum, the model allows a physician to transfer patients to a more advanced hospital but at a cost in terms of health severity. Doctors choose to do so whenever the expected return in terms of survival probability is high enough to make the investment worthwhile. The model shows that reducing the transfer cost (by improving coordination) would increase transfers and improve survival among more complicated patients and that improving capabilities would lead to less transfers and improved outcomes for every patient.

Based on the reduced-form estimates, I back out the structural parameters of the model and use them to perform counter-factual policy analysis. I conclude that the facilitation of across-hospital transfers through better communication would have provided 67% of the total effect alone, but with substantially more transfers. Moreover, I document that both components are substitutes as the capabilities component would have induced 65% of the effect. The components substitute each other because patients that are transferred cannot experience the benefits of better service at the sending hospital.

To my knowledge, this is the first paper to directly observe the role that technology adoption can have on coordination across hospitals and is the first project to evaluate the effect of adopting ICT in a developing country context. Moreover, the project highlights the role that widespread and widely accessible technologies can play in improving healthcare. The last point is relevant for developed countries as well since some hospitals are exploring apps to increase communication speed. [2]

The remainder of the paper is organized as follows. Section 2 describes a literature review. Section 3 describes the background of the IMSS system and the CI program. Section 4 discusses the data. Section 5 conducts our main DID estimations. Section 6 explores the channels through which each component of the program may have contributed and presents the model for interpreting the DID results. Section 7 provides some concluding remarks.

2 Literature Review

This paper contributes to the literature on the effects of fragmentation on outcomes. (Agha et al., 2019) shows that patients who move to a more fragmented region utilize more services and substitute away primary care. (Kellermann and Jones, 2013) argues that one of the main reasons why the health IT promise to save billions of dollars and improve healthcare is because IT systems are inoperable across providers. Could lack of communication explain bad outcomes? This project is the first to analyze the effects of reduced fragmentation across hospitals on health outcomes.

This paper also contributes to the vast literature on the effect of ICT on health outcomes by providing evidence of high returns to simple technology improvements in the developing country context. (Atasoy et al., 2019) provides an overview of why ICT should go a long way in improving health outcomes. While the medical literature finds mostly positive effects, the economics literature shows substantial heterogeneity across settings, technologies and populations analyzed. For example, (Agha, 2014) shows, based on Medicare data, that electronic health records do not improve outcomes but increase spending. However, (Miller and Tucker, 2011) show that infant mortality is reduced as a consequence of health IT. Moreover, (McCullough et al., 2016) shows that IT helps some patients but not all, with benefits going mainly to more complicated patients. (Parente and McCullough, 2009) look at 3 technologies: EHR, picture archiving and communication systems and find that only EHR has a clear effect of

[2] Mount Sinai launched a mobile app to optimize care for heart attack patients that relies on the same mechanisms as the CI program, https://www.mountsinai.org/about/newsroom/2021/mount-sinai-launches-mobile-app-to-optimize-care-for-heart-attack-patients

improving patient safety while (Athey and Stern, 2002) find that the adoption of ICT at emergency call centers in the US that link caller identification to a location database resulted in an increased survival rate for heart attack patients. (Bronsoler et al., 2021) presents an in-depth review of both the economics and medical literatures, which contains several meta-reviews.

This paper also contributes to the literature on the effect of better management practices on outcomes. To the extent that the CI program can be regarded as better management practice, I establish a direct causal link between better management quality and better patient health outcomes. While there is no other paper that links management practices to health outcomes directly, there have been several studies that highlight the importance of management practices on productivity (for a review read (Bloom and Van-Reenen, 2011)). Health IT is particular because healthcare staff are often resistant to change and implementation of new technologies often fail (review in (Gnanlet et al., 2019)). This paper highlights that implementing health IT initiatives based on already existing widespread technology could avoid the lack of buy-in problem.

This paper also contributes to the literature on efficient allocation of patients to hospitals as CI changes patient allocation within treatment networks. (Dranove et al., 2003) finds in the US context that publishing information on a hospital's performance leads to changes in patient selection, as higher scored hospitals receive patients with worse conditions. Likewise, (Bloom et al., 2013) conclude that hospital competition leads to better management quality by hospitals and better health outcomes for patients in the UK. Other related studies include (Chan, 2015), who finds that teamwork by doctors increases medical outputs by reducing moral hazard, and (Chandra and Staiger, 2007) that argues that hospitals that are better at intensive treatment are better able to treat individuals in need of such attention. We analyze one implication of such heterogeneity via the impact of ICT; i.e., could we affect patient outcomes by changing the patient-hospital allocation?

Lastly, my paper is, to the best of my knowledge, the first to analyze in depth the effect of a program like "Código Infarto". Some medical studies have studied the relationship between lower time to treatment and mortality ((Cannon et al., 2000), (McNamara et al., 2006), (Lambert et al., 2010), (Menees et al., 2013), (Wang et al., 2011) , (Dauerman et al., 2015)) and some others have evaluated similar programs through pre-post strategies, including an evaluation of Codigo Infarto in Mexico ((Gómez-Hospital et al., 2012), (Cordero et al., 2016), (Borrayo-Sánchez et al., 2017)). However, none of this studies offer a causal estimation of the effect, an explanation on the mechanisms through which the program is working nor an explanation for why it has heterogeneous effects across hospitals.

3 IMSS and the "Código Infarto" (CI) Program

Health care in Mexico is provided primarily by several public sector institutions. The largest is Instituto Mexicano del Seguro Social (IMSS), the single payer insurance plan for formal sector workers in the country. This program covers formal workers and their families as well as students but also offers a voluntary enrollment option which makes up under 1% of beneficiaries. Every private employer that hires a new employee is required to enroll him/her to IMSS. This service is paid for in 3 parts: On average, the government contributes 5.3% of employees base wages, employers contribute 16.5% and employees another 2.5%. [3] IMSS runs its own 1522 primary care clinics, 256 acute care hospitals, and 36 specialty hospitals. Smaller but similar public options exist for particular sectors such as government workers (ISSSTE), the navy (SEMAR), the army (SEDENA), and for workers of the state-owned oil company (PEMEX).[4]

IMSS is Mexico's largest health care provider. It is also the country's largest health insurer, with over 70 million beneficiaries. IMSS's medical networks are organized over three levels. Primary care clinics treat regular illnesses that do not require complicated surgery, general (low-specialty) hospitals treat almost all illness and provide surgery services for beneficiaries, and high specialty hospitals treat the most complicated cases and are equipped with cutting-edge technology. Each IMSS beneficiary is assigned to one first-level unit determined by their location of residence. Each first-level unit is then ascribed to a second-level hospital, which in turn is assigned to a specialty tertiary unit. IMSS' heart attack treatment structure is organized in 23 networks, each with several general hospitals and one reperfusion center hospital where severe patients can be transferred to if they need advanced procedures. Figure 2 shows a map of the location of each of IMSS' networks and a close up of how Mexico City, with both its networks looks.

A heart attack occurs when the flow of blood to the heart is blocked. The blockage is most often a buildup of fat, cholesterol and other substances, which form a plaque in the arteries that feed the heart (coronary arteries). When the plaque ruptures, it can form a clot that blocks blood flow, causing a heart attack. The interrupted flow deprives the heart from oxygen, which causes it to start dying. Treating a heart attack promptly at a hospital is key to avoid its worst outcomes. When a patient experiences a heart attack, she can be given fibrynolitic therapy (FT) or a percutaneous coronary intervention (PCI). FT consists of drugs that help the body dissolve clots and is widely available. PCI is a more complicated procedure that consists of inflating a balloon where the narrowing of the artery occurred and installing a stent that enables it to stay unblocked. The latter procedure needs to be performed by a specialist and

[3] Law of Social Security.
[4] (IMSS, 2020)

not every hospital can do so, but allows complicated patients to survive.

Regardless of the procedure, when a patient has a heart attack, it is important to minimize the time without treatment. The 2013 American Heart Association (AHA) guidelines suggest a 30 min door-to-needle (FT) and a 90 min door to balloon (PCI) for patients. The idea is to try and send the patient with a heart attack to a PCI enabled location in less than 120 minutes or, if that option is not feasible, apply FT in the first 30, stabilize the patient and evaluate a potential transfer over the next 24 hours (O'gara et al., 2013). Figure 3 summarizes the algorithm. Getting to treatment quickly makes a big difference, (Scholz et al., 2018) estimates an increase of more than 3pp in the likelihood of dying for every additional 10 minutes that a patient with cardiogenic shock takes to get to the reperfusion center.

Código Infarto (CI) has the aim of improving the time between a patient showing up and treatment being provided, ultimately reaching the timeline proposed in the AHA guidelines. To achieve these goals, CI comprises a set of simple interventions. On the one hand, across hospitals, the program created chat groups between doctors at general hospitals (GH) and reperfusion centers (RC) so that they can communicate efficiently and coordinate transfers better, a notably cheap intervention. Building on the app's infrastructure, physicians are able to share ECG scans and share clinical information quickly. On the other hand, within hospitals, the program improves urgent wing's procedures on low-specialty hospitals by clearly labeling the room where heart attack patients should be treated and prioritizing its use for such ailments as well as by providing training on main heart attack symptoms to all the staff (security, cleaning, etc.) and instructing everyone to help incoming individuals with potential heart attacks get attention quickly.

Prior to the program launch, to transfer a patient, a doctor had to call the PCI-hospital, talk to a secretary and explain the need to talk to a physician, wait for that person to get hold of someone and then make the argument of why such a patient needed a transfer over the phone. Moreover, after getting transferred and getting to the reperfusion center, the patient would be assigned to the next available physician in the urgent wing. After all of that, the urgent wing doctor would read through the notes made at the general hospital for the first time and would potentially order additional tests to assess the patient's status before treatment. Through the chat group, doctors are able to share ECG scans and diagnosis so that anyone who receives the patient can treat her with complete information. Also, urgent wing physicians are alerted of an incoming heart attack patient and can prepare before arrival to provide treatment. Figure 4 describes the improvements induced by the CI program.

In summary, as shown in Figure 4, the CI program improves medical attention through two different components. First, it improves hospital capabilities to treat heart attacks by prioritizing attention for heart attack patients in the triage and training all staff members on symptoms. Second, it improves transfers from non-PCI capable hospitals to PCI-capable hospitals by increasing the flexibility and efficiency of transfers through communication and coordination (better ICT).

CI was first launched in February 2015 in Mexico City's south medical network as a pilot program for its eight second-level hospitals and one PCI-capable hospital, where the program designer was cardiology head. After encouraging observataions from the pilot network, by Summer 2018, the program had expanded to all 23 networks. In each of them, a PCI capable hospital oversees others and receives transfers. Overall, the program is now running on 191 hospitals across the country. Table 1 describes the dates of implementation for each network and how many hospitals it has.

4 Data

To analyze the effect of the CI program, I utilize medical case-level data sets from IMSS. Overall, by combining different sources within the institute, I am able to track the full story of every heart attack patient that went to an IMSS urgent wing between January 2013 and December 2019, the target population of the study. A key advantage of IMSS' systems is that they all rely on a social security number combined with an intra-family id to identify an individual, which allows them to identify and match individuals across datasets. Taking advantage of this, I have all the medical information from patients who were diagnosed with a heart attack at the urgent wing, including their hospitalization history and IMSS' death census.

The first source of information is the urgent wing administrative data for heart attack patients that went to an IMSS urgent wing. These dataset contains cases who were diagnosed with an acute myocardial infarction (heart attack) at the urgent wing and contains information on hospital of entry, date and time of entry, date and time of exit, the patient's age and sex and whether the patient died before leaving the hospital. [5] Over the analysis period I have 95,447 different entries. I define mortality as whether the patient died during the following 10 days after first admission and consequently define a case length to be 30 days from first appearance. Since patients usually go through the urgent wing at the receiving hospital after transfers, some cases appear more than once. After cleaning for double appearances I have 80,539 cases.

The second source of information I utilize are the hospital admission records for heart attack patients. This data is similarly filtered and contains of 94,327 entries with information on hospital of admission, date of entry and exit (but not time), as well as whether the patient died at the hospital. To be able to match this information to the urgent wing data, which is at the case level, I reshape it into a wide table that captures every date of entry and exit as well as whether the patient died for each heart attack a patient was admitted for. I end up with 87,152 different patients.

[5] Based on an ICD-10 diagnosis that starts with I21.

In order to combine both datasets I do a many to one match from the urgent wing data into the hospital data and define an appearance as relevant whenever the date of entry is under 30 days away from the first appearance of the case in the urgent wing. I then move on to define an individual as transferred whenever they appear at a reperfusion center (hospital or urgent wing) after starting in a general hospital and define a patient as a survival case whenever they have not died during the first 30 days since entering. I identify 5,313 (7%) patients who were transferred, with 70% appearing in the urgent wing data in the receiving hospitals [6]. Moreover, there are 21,769 deaths (27%), with 91% appearing in the urgent wing data. The last step to complement the death dummy is to incorporate the death census data from IMSS, which captures out of the hospital deaths. I find an extra 3,640 relevant deaths, an extra 17%.

With these three data sets, we can observe the entire history of each heart attack that arrived to an IMSS urgent wing and estimate the program's effect. One limitation of the data I have is that I do not have detailed data on the heart-attack characteristics each patient had. That is, I can not observe directly from the data the severity of each case. This limits us to make assumptions on doctor's decisions. Table 2 presents descriptive statistics of the data. We can see that average survival rate is 68%, with 82% after arriving to RCs and 60% when arriving to GHs. Moreover, 11% of patients are transferred on average and it takes 12 hours to execute a transfer. The average patient is 66 years old and 66% are male.

5 Reduced Form

5.1 Empirical Strategy and Program Effects

In this section I describe the empirical strategy utilized to analyze the effects of the program and the results obtained. Since there is staggered implementation of CI, utilizing a simple two-way fixed effects model could lead to bias because of potential negative weighting. The main reasoning behind this comes from the fact that if there would be dynamic effects on our treatment units (hospitals), we would be comparing a treatment unit to a control that is still being affected by its own treatment. Before explaining the stacking procedure utilized to evaluate the program as a whole, I first describe a simple Differences in Differences (DID) design on Mexico City's networks as a motivating example.

Mexico City, because of its size, has 2 full networks: South and North. As mentioned before, the program was first implemented in Mexico city's South network in February 2015 and then gradually expanded to the remaining 22. The 2 reperfusion centers in Mexico (Siglo XXI and La Raza) are the biggest medical centers in the IMSS network and compete to be the best hospital in the country, with an

[6]Some cases are not registered because after transfer the patient is directly admitted

87% and 85% heart attack survival rate respectively. Moreover, the only reason why the program started in the south and not the north is because the program designer was cardiology chair in the south at that time. D.F North started the program early October but preparations were underway a month before, so I utilize data from the 3,654 heart attack cases between July 2014- August 2015 in these 2 networks to evaluate the programs within Mexico City.

I utilize the following specification to estimate the effects:

$$y_{i,h,t} = \alpha_h + \gamma_t + \beta(T_h * Post_t) + \epsilon_{i,h,t}$$

where:

- $y_{i,h,t}$ is the outcome for case i in hospital h on time t.
- α_h are hospital fixed effects.
- γ_t are month fixed effects.
- $T_h$is a dummy for whether the hospital is in the south network.
- $Post_t$ is a dummy marking if the case started on or after Feb 2015.

Table 3 showcases the results. We can see that there is a 10 pp (20%) increase in survival rate for patients that arrive first to a general hospital. Moreover, we can see that there is an increase in the transfer rate of 6.5 pp (60%), but no evidence of a reduction in transfer times (although I am dramatically underpowered for this exercise). Lastly, we can see that the program had no negative effect on patients that arrived directly to the RC. This was a big concern of the program as increased demand could have induced a negative externality. Figure 5 reports the event studies for survival and transfers. Table 4 validates the strategy by showing null results when conducting a placebo test where I shift the implementation date to 12 months earlier.

Analyzing the full program has several advantages. It enables us to asses if the program's effects are the same across hospitals and networks and gives us enough power to look for heterogeneous patterns and understand potential mechanisms behind it. To be able to do this, I do a stacking procedure which eliminates the potential risk of negative weighting under TWFE estimation. In particular, I follow (Deshpande and Li, 2019). The main idea is to create a dataset that encompasses all treatments on the same timeline and thus removes the possibility of incorporating dynamic effects into the treatment/control comparisons.

The way to achieve this is to first create a unique dataset for each treatment starting time and normalize time for both control and treatment groups around the start of the intervention. In each of these datasets one should include only viable control groups, in the sense that they are not affected by treatment dynamics. Including eventual adopters who have not yet adopted is standard in the literature, and is what I do. Once these datasets are created, one should stack them together. Note that some observations could be repeated in this final dataset. The last step is to run DID specifications that control for expansion/unit fixed effects and relative time to program start within each observation (time to intervention start). For my particular case, I create 23 separate datasets and include as viable controls heart attack cases from networks who will be treated but will not receive CI during the following 8 months. The period I focus the analysis on is 6 months after intervention and 7 months before, following the DF DID analysis presented above.[7]

The final dataset consists of 68,007 heart attack cases with 15 networks that we estimate an effect for. [8]. Table 5 shows descriptives statistics of the new dataset. Overall, we can see that heart attack cases are similar to the ones described in table 2. 13% of patients are trasferred, overall survival rate is 66% with general hospitals showing a 62% survival rate and reperfusion centers a 75% rate. The latter reflects the fact that the reperfusion centers in Mexico city are the best hospitals in the IMSS network. Lastly, individuals are 65 years old on average and 65% are male.

In order to analyze the intervention I utilize the following specification::

$$y_{i,h,e,t} = \alpha_{h,e} + \gamma_t + \sum_{\tau} D^{\tau}_{e,t} + \beta(T_{h,e} * Post_{e,t}) + \epsilon_{i,h,e,t} \tag{1}$$

where:

- $y_{i,h,e,t}$ is the outcome for case i in hospital h at expansion e on time t.
- $\alpha_{h,e}$ are hospital-expansion fixed effects.
- γ_t are month fixed effects.
- $D^{\tau}_{e,t}$ are dummies equal to one if the case is τ months away from CI in the specific expansion.
- $T_{h,e}$ are the treatment units in each expansion.
- $Post_{e,t}$ is a dummy marking when $D^{\tau}_{e,t} \geq 0$

And the event study equivalent:

$$y_{i,h,e,t} = \alpha_{h,e} + \gamma_t + \sum_{\tau} D^{\tau}_{e,t} + \sum_{\tau} \beta_{\tau}(T_{h,e} * D_{e,t}) + \epsilon_{i,h,e,t}$$

[7]Varying this time selection does not affect the results.
[8]Last adopters have no viable control group

Table 6 presents the results. We can see that the program had a substantial effect on survival rates, with an average effect of 3.7pp (7%). Moreover, we see an increase in transfers of 2.5pp, (24%). Interestingly, after getting additional power we now find a huge reduction in times to transfer of 4 hours out of a mean of 12. That is, the program reduces time of transfer by 33%. Lastly, we see that there is no negative externality on the reperfusion centers. In fact, the estimate is positive. Figure 6 reports the event study estimates for this exercise where we can see there are no pre-trends. Moreover, Table 7 presents a placebo exercise where the start date of the program is shifted 12 months for each network. We see null results in this specification.

Understanding whether the effect of the program is constant across hospitals or whether there are some key characteristics on which the intervention works better is relevant from a policy perspective. Especially when considering the implementation of a similar policy. In a similar vein, it would be extremely important for a policy maker to understand whether the impressive effects that the program has are driven by the simple communication component or by the more involved improvement in capabilities. I now move on to analyze heterogeneity first and then move forward to disentangle the contribution of each component.

5.2 Heterogeneity

There are 2 sources of heterogenity that may be driving a different response by hospitals to the program. On the one hand, whether there is much to gain or not from transferring a patient. If a general hospital is almost as good at treating patients than its reperfusion center, or its reperfusion center will not provide a timely PCI, then there may be not much to gain from improving communication and coordination. On the other hand, the distance from a general hospital to a reperfusion center could matter quite a lot since a transfer from a farther place would take longer.

To assess whether the difference in capabilities plays a role, I define skills through the pre-CI mean survival rate for patients that arrive to each hospital and define a skill gap as the difference between the skill at a general hospital and its reperfusion center in the pre-period. Moreover, Taking advantage that I have the geographic coordinates for each IMSS clinic, I am able to calculate the distance from every general hospital to its reperfusion center.[9]. Figure 7 reports the histograms for both measures where we can see that there is significant variation. The median general hospital faces a 10% skill-gap and its reperfusion center is 80 km away.

In order to empirically test whether each of these components matter, I run a DID specification similar to equation 1 but including an interaction term between Tpost and the mechanism being

[9] Time of transportation yields similar results

explored. Table 8 presents the results. We can see that there is a clear and strong correlation between skill gap and size of effect, where general hospitals with a larger skill gap experience a larger effect. Moreover, we can see that there is no correlation of the effect with distance. suggesting that this is not a key driver of heterogeneity. Figure 8 reports the event studies for both interaction terms, where this pattern is even more apparent.

To further understand which hospitals are driving the effect, I classify treated hospitals into 3 categories based on skill-gap terciles: low, medium, and high and replicate the analysis but including interactions between Tpost and each of the categories. Table 9 reports the findings. We can see that there is an even larger effect among hospitals with a large skill-gap but no effect among the rest of them. Among these hospitals we find an increase of 12pp (29%) in survival and 5pp (86%) in transfers. Interestingly, though, we do find an effect on transfer times for every hospital.

These findings suggest that the program proves extremely effective whenever there is a lot to gain from transferring patients, which is consistent with the communication channel mattering more. However, in order to separate the contribution of each component we need to find a way that accounts for the effect of the program on transfer selection. As shown in table 10, when analyzing the effect of the program conditioning by whether the patient was transferred or not, we see that most of the effect is coming from patients that do not get transferred.

we cannot fully disentangle which component of the program is driving the results because the program affects selection. On the one hand, when the general hospital becomes more capable there is lower necessity to transfer patients. This will in turn lead to less transfers. On the other hand, whenever communication costs are lowered, transfers become easier. One would expect that in this scenario there would be more transfers and the patients transferred would be more severe than they were before since transferring is now feasible. In order to properly disentangle these components I develop a structural model where doctors need to choose whether to transfer a patient for treatment or not accounting for costs of transfers in terms of health below.

6 Mechanisms

Understanding the role that each component of the program plays in the positive survival rate and how they interact is important when drawing lessons from the large effects. For example, if the ICT channel is responsible for most of the improvement, extending and replicating in other contexts should be relatively easy. Moreover. if both components complement each other, one would probably think about how to implement them together, but if they substitute each other one could probably get similar returns by choosing one or the other. In this section I first discuss potential mechanisms of the program and then present a model that allows me to disentangle each component's contribution.

On the one hand, cheaper communication leads to more transfers and there are two ways through which an increase in transfers can increase the survival rate for heart attack patients that arrive to general hospitals: By reducing overcrowded urgent wings and thus allowing doctors to be more focused on each patient and by allowing patients to get more specialized treatment at the RC faster. The latter affects patients selected for transfers as lower costs means that more severe cases can make the trip. I can empirically discard the former as Out of the 65,000 cases in general hospitals in our final sample, 54 percent where the only heart attack case a low-specialty urgent wing had on the whole day. Further, only 9 percent arrived within less than 4 hours of space from the previous patient and 5 percent with less than 2 hours. Note that this does not say that resources could not be limited for such patients, it just shows that the transfer increase is unlikely to have played a role. Similarly, a potential negative externality of the transfer effect is that such a large increase in transfers may have affected the performance of high-specialty hospitals as the rise in incoming patients could divert resources previously devoted to high-specialty arrival patients. However, as shown before, there is no negative effect of the program for patients that arrive directly to the RC.

On the other hand, when all the staff is trained to react and heart attack patients are given the maximum priority within the urgent wing, we can imagine that translates into patients receiving better treatment. Increasing capabilities for general hospitals, however, also impacts transfer selection. relatively easy cases that required transfers may not require it anymore. Moreover, patients who were on the line between transfer or not because of the risks implied will probably now stay for treatment in the GH. Thus, this component should squeeze transfers in the middle. On the following section I develop a model that allows me to identify and disentangle the role and contributions of each component.

6.1 Model: In-hospital logistics and ICT improvements

I introduce a model that enables a deeper understanding of the effects presented in the previous section. The model showcases the decision that physicians at general hospitals face on how to treat a heart-attack patient. In sum, the model allows a physician to transfer patients to a more advanced hospital (RC) but at a cost in terms of health severity. Doctors choose to do so whenever the expected return in terms of survival probability is high enough to make the investment worthwhile. The model is consistent with the mechanisms discussed before. Easiest patients will not require transfers and most complicated patients will not be able to get them. Moreover, Reducing the transfer cost (by improving coordination) would increase transfers and improve survival among more complicated patients while improving capabilities would lead to less transfers and improved outcomes for every patient. I first describe the assumptions and then explain the forces behind the model.

6.1.1 Assumptions

1. Each heart attack patient i has severity level δ_i, and $\delta_i \in [0, 1]$.

2. Each hospital has capabilities λ_j, with $\lambda_j > 0$. We assume 2 kinds of hospitals, general hospital (GH) and reperfusion centers (RC) specialties. With $\lambda_{GH} < \lambda_{RC}$.

3. Each hospital/patient combination match into a survival probability function $S(\delta_i, \lambda_j)$ where survival probability increases with hospital's capabilities and decreases with patient's severity. Mainly:

   - $\frac{\partial}{\partial \delta_i} s(\delta_i, \lambda_j) < 0$
   - $\frac{\partial}{\partial \lambda_j} s(\delta_i, \lambda_j) > 0$
   - $S(0, \lambda_j) = 0, S(1, \lambda_j) = 1$

4. Transfer of patients is possible, but not free. We assume there is a fixed cost c in terms of severity, patient i with initial level of severity δ_i becomes $\delta_i + c \cdot \delta_i$ after transfer. This is because transferring a patient takes additional time before attention, which worsens health conditions. Now, since this effect is bigger the more severe a patient is, we assume that it grows proportionally to initial severity.

5. Lastly, there is a threshhold κ which hospitals use to detrermine whether a transfer is worth it. Mainly, a patient is transferred from hospital GH to RC if $S(\delta_i + c(\delta_i), \lambda_{RC}) - S(\delta_i, \lambda_{GH}) > \kappa$. The κ parameter captures that a patient would probably not be transferred if the return to doing so was very low.

6. In order to keep the functional form flexible, we assume that $S(\delta_i, \lambda_j) = 1 - I_{\delta i}(\lambda_j, \alpha)$ where $I_{\delta i}(\lambda_j, \alpha)$ is the CDF of a beta distribution. This assumption enables the survival probability function to take several shapes that satisfy the above requirements and does not force me to make any concavity/convexity assumptions. Figure 9 shows some of this potential shapes graphically. Critically, given α, the higher the value of capabilities, the better the patient does and the higher the δ, the worst the patient does. Figure 10 presents how the survival function looks for several potential values of λ_j once α id fixed. We can see that when λ_j is really small the likelihood of survival is really low and becomes bigger as λ_j increases, with a higher λ_j always dominating a smaller one. Moreover, we can see that the whole space is covered by dirrerent functions since λ_j is continuous.

6.1.2 Understanding the model

To get a better sense of why the model can help explain the CI program contributions it is important to understand the driving forces behind it. In this subsection I go in depth to explain the mechanisms working in the model. Let us think through how the decision to transfer a patient looks. A patient could benefit of being transferred from a general hospital to a reperfusion center if the probability of survival is better, even after accounting for the cost of transfer in terms of severity. Since the transfer cost is increasing with severity, then the most complicated patients will not be able to be transferred. Moreover, the least complicated patients would have a slight benefit of transfer, even though their chances of survival are pretty high anywhere. Lastly, for the patients in the middle the benefit of transfer is going to be bigger since they are the ones that could really benefit from gaining access to more advanced technology and can withstand the ride there.

Doctors have to think about whether each patient's transfer is worth it. In the model, a patient will be transferred to a reperfusion center if the survival probability he faces after transfer is at least κ higher than what he faces if he stays. Figure 11 shows these patterns. There are 4 lines in the image. The Blue line with long dashes captures the survival function for GH. The red line represents the survival function that RC face. It dominates the blue line since $\frac{\partial}{\partial \lambda_j} s(\delta_i, \lambda_j) > 0$. The purple dotted line reflects the survival probability that a patient would face after transfer: $S(\delta_i + c \cdot \delta_i, \lambda_{RC})$. We can see that this line is lower than the RC because of the cost that has to be paid for transfer. Moreover, the difference increases as severity δ_i increases, since more complicated patients experience a higher cost. The purple line with long dashes highlights the transfer decision curve. This line represents the survival probability after transfer but displaced by κ downwards. That means that whenever the transfer decision line is above the blue line, a transfer will be worth it. The purple rectangle highlights such patients.

The model reflects that it is reasonable for doctors to transfer individuals that have a substantial benefit from transfer. If every patient with a small benefit would be transferred, then physicians would request an ambulance to transfer many people with headaches in the off chance it could be something else. The model shows that transfers always happen in the middle if $\kappa > 0$. We can see that the higher κ is, the more that transfers shrink towards the center. We now move forward to shifting the model according to the components of the program.

The first component of the program is an improvement in coordination through more efficient communication. The creation of the group chats should reduce the time it takes for a patient to get transferred and thus reduce the c within the model. Figure 12 highlights the role of this channel. On the figure we can see the same 4 lines from 11 in red along with how the survival if transfer and transfer decision lines would look under a lower c. We can see that patients would now face a bigger survival probability after transfer, especially among more severe patients. This happens because the cost is increasing in terms of severity and thus a reduction inc yields higher benefits for them. We can see that there would be additional transfers and that those transfers would be focused on more severe cases as a consequence of this mechanism.

Figure 13 highlights the benefit in terms of survival for a patient who was not transferred before and would be transferred now. The image shows a substantial change in probability of survival for such a patient. The mechanism driving this is that if the cost of transfer is relatively high, as for this patient, a transfer becomes too expensive in terms of health and the patient cannot get the benefits of better treatment. Conversely, the mechanism is not important for the least transferred patients as the transfer cost in terms of health poses a minimal risk to their survival, regardless of c.

The second component of the program is an improvement in capabilities of the general hospitals. This improvement is reflected in the model by a higher λ_{GH}. Figure 14 highlights what happens. The figure highlights the same 4 lines from 11 in red along with how the shift in capabilities for general hospitals in blue. We can see that the shift induces a slight improvement for patients across severities and reduces transfers towards the middle. This pattern reflects that least and more severe patients who were just transferred no longer present a worthwhile investment in terms of health for the doctor.

Based on these mechanisms one can now understand why the skill-gap is such an important driver of the program's success. If there is very little skill gap between general hospitals and reperfusion centers, there will be small gains from transfers, even when costs are 0. Moreover, if costs are high but there is still a significant skill-gap, the communication channel could still induce a positive change. That is, even if the general hospital is far away and thus has a large c, reducing it could still help quite a lot. Hence, the pattern we observe in the data is to be expected. The next section estimates the model based on the data and interprets the reduced form through its lens.

6.1.3 Taking the model to the data

The model described above allows us to disentangle both mechanisms of the program. However, In order to be able to run counterfactual policy analysis we need to be able to identify the structural parameters based on the data first. Note that the model has 5 parameters $(\lambda_{GH}, \lambda_{RC}, c, \kappa, \alpha)$. Moreover, since the intervention potentially affects capabilities at the GH and RC hospitals and the cost of transfers in terms of health we end up with 8 parameters to estimate in total: $(\lambda_{GH0}, \lambda_{GH1}\lambda_{RC0}, \lambda_{RC1}, c_0, c_1, \kappa, \alpha)$. Therefore we need 8 data moments along with an estimation of the severity distribution to estimate our results. In order to estimate the structural parameters of the model we utilize the following moments in the data:

1. $Y_{RC,0}$- the survival rate for RC arrivals before CI.

2. $Y_{RC,1}$- the survival rate for RC arrivals after CI.

3. $Y_{GH,stay,0}$- the survival rate for non-transferred GH arrivals before CI.

4. $Y_{GH,stay,1}$- the survival rate for non-transferred GH arrivals after CI.

5. $Y_{GH,tr,0}$- the survival rate for transferred GH arrivals before CI.

6. $Y_{GH,tr,1}$- the survival rate for transferred GH arrivals after CI.

7. TR_0- the transfer rate before CI.

8. TR_1- the transfer rate after CI.

These gives us 8 structural parameters and 8 moments in the data. Now, in order to avoid getting bias and capturing shifts that are not coming from the intervention, I define the moments before the intervention based on the pre-CI mean for the treatment group and define the post intervention moments as the moments before shifted by the reduced from estimates from section 3. Table 11 shows the moments we utilize. with these moments, I estimate the model through GMM with the following vector of moment conditions $\mathbb{E}g = 0$:

1. $\mathbb{E}\left[S(\delta_i, \lambda_{RC}, \alpha) - y_i | \text{RC}\right] = 0$

2. $\mathbb{E}[\mathbf{1}\{S(\delta_i + \delta_i \cdot c, \lambda_{RC}, \alpha) - S(\delta_i + \delta_i \cdot c, \lambda_{GH}, \alpha) > \kappa\} - tr_i | \text{GH}] = 0$

3. $\mathbb{E}[S(\delta_i + \delta_i * c, \lambda_{RC}, \alpha) - y_i | \text{Transfer}] = 0$

4. $\mathbb{E}[S(\delta_i, \lambda_{RC}, \alpha) - y_i | \text{GH, no transfer}] = 0$

5. $\mathbb{E}\left[S(\delta_i, \lambda_{RC}, \alpha) - y_i - \hat{\beta}_1 | \text{RC}\right] = 0]$

6. $\mathbb{E}[\mathbf{1}\{S(\delta_i + \delta_i \cdot c, \lambda_{RC}, \alpha) - S(\delta_i + \delta_i \cdot c, \lambda_{GH}, \alpha) > \kappa\} - tr_i - \hat{\beta}_2 | \text{GH}] = 0$

7. $\mathbb{E}[S(\delta_i + \delta_i * c, \lambda_{RC}, \alpha) - y_i - \hat{\beta}_3 | \text{Transfer}] = 0$

8. $\mathbb{E}[S(\delta_i, \lambda_{RC}, \alpha) - y_i - \hat{\beta}_4 | \text{GH, no transfer}] = 0$

Where y_i denotes survival, tr_i denotes transfer and $\hat{\beta}_i$ denotes the reduced form estimate of the CI effect on the data moment.

The last thing missing before being able to estimate the model is getting the severity distribution. In order to do this, I adapt different machine learning prediction models of mortality. In particular, I utilize 2014 as a baseline training year for every heart attack since the CI started being implemented until February 2015. Taking advantage of the fact that I have data for every hospitalization that IMSS had since 2013 until 2019, I create a model that incorporates every hospitalization that a person with a heart attack had in the 12 months prior to the event, how many nights he spent in the hospital over the last year, which ICD-10 code was the person hospitalized for along with demographic variables such as age and sex and hour of entry, day of the week of entry, and month of entry. Importantly, in order to prevent skill information from polluting the estimation I refrain from utilizing any location variables. After training the model with data from 2014, I use it to predict mortality in following years. Table 12 shows the mean squared errors (MSE) I obtain from such exercise. We can see that all methods behave almost equally well. Figure 15 reports the histogram for the Lasso prediction which is what I use as severity from now on. [10]

Based on the above equations I estimate the structural parameters. In order to do so, I define a function that penalizes quadratically for deviations in each of the 8 core moments that we have and minimize such deviations using the optim package from R. Table 13 reports our estimations. As expected, there is a slight improvement in general hospitals' capabilities from 1.8 to 2.2 and a pretty big improvement in terms of transfer costs as the parameter goes down from 1.6 to 1. That means that the cost of transferring a patient went down by nearly 40%. Moreover, we can see that the threshold for transferring a patient is estimated at 0.15. That is, a doctor considers a transfer worth it if the probability of survival is at least 15% higher after transfer.

To understand what is happening further and whether the model adjusts well to the data we compare whether the transfer pattern and its movement predicted by the adjusted structural parameters replicates what we see in the data based on the lasso prediction. figure 16 presents how the adjusted model looks before and after CI. The pre period adjusted model is shaded. Overall, the graph shows that there was virtually no change in RC capabilities, that there was a slight improvement in GH skills and that the transfer cost decreases significantly. Moreover, the figure shows that as a consequence of these changes, more complicated patients are now being transferred than before: with more complicated patients now being able to be transferred and some easier patients now not requiring a transfer.

To assess the model's explanatory power, we can compare its predictions to the transfer patterns that are observed with the estimated severity, which we can observe without imposing anything. Figure 17 reports a figure for the transfer pattern before and after. We can see that the transfer pattern is concentrated in the middle, as the model predicted. Moreover, we can see a shift to the right in the transfer distribution which is consistent with the model's prediction of the program's effect. On the one

[10] Results are very similar with any other estimation reported.

hand, we see that there are additional transfers for more complicated individuals and, on the other, we see that there are less transfers for the least complicated ones. These comparison suggests that the model is well equipped to explain the intervention's mechanisms. We now move on to use the model to assess each component's contribution.

6.1.4 Counterfactual Policy Simulation

Taking advantage of the structural parameters estimated we can do cuonterfactual policy estimation. That is, we can ask how much of the contribution would have happened if the capabilities component of the program would not have been included in the CI program. In order to do this, I calculate the survival probability before the intervention using the parameters we get from the model and then I repeat the exercise but changing c_0 for c_1. Figure 18 reflects how the model shifts. We get an improvement of 8 percentage points in terms of probability of survival, which is 68% of the effect. Moreover, we get that transfers would have been at a 40% rate. Substantially more than what we observe in the data.

I also do the same exercise to see the contribution that the capabilities component would have had alone. Figure 19 shows this exercise. What I find is a comparable increase at 7.5 percentage points (64% of the total) without the communication channel. This highlights that the capabilities improvement was effective as well. Under this scenario, we find that no transfers would take place because the increase in capabilities makes every transfer too expensive to do. This would be a consequence of keeping high cost but reducing the skill-gap between sender and receiver.

The fact that the sum of each components contribution equals 132% of the total effect highlights that the communication and capabilities channels are substitutes. Since the main benefit from the communication channel is coming from the fact that some patients are now transferred to a more advanced center, they would not be able to take advantage of the improved services at the general hospital they will not use. Similarly, the benefit from improved coordination will not be received by patients who will not require a transfer given the simultaneous increase in capabilities.

The lessons drawn from this analysis highlights some interesting takeaways for policymakers. First, the communication channel is extremely easy to implement and whenever there is a large enough skill-gap, it would probably be effective. Second, whenever applying a reduction to communication barriers, one should be aware of the induced increase in transfers and make sure that there is enough supply to handle increased demand. Third, increased capabilities can also be effective and leads to a reduction in transfers. Fourth, given that both components are substitutes, policymakers should consider which is the best fit for their context before making a decision. Generally, when there is large fragmentation and a substantial skill-gap, the communication channel probably has a higher return. However, when there is little skill-gap or no room for additional demand of transfers, an investment in capabilities might be worthwhile.

7 Concluding Remarks

Over the past few decades several nations have stressed the use of information and communication technology (ICT) in healthcare as a mechanism to improve efficiency and clinical outcomes. However, after spending several billions of dollars to try and achieve a centralized electronic health record with health information exchange capabilities, the literature suggests small effects with vast heterogeneity. One of the main hypothesis for this is that the systems do not communicate well. This project addresses a simple yet powerful idea on how to improve coordination: leveraging widespread technologies.

In particular, the paper evaluates the "Código Infarto" (CI) program implemented by Mexico's largest healthcare provider. CI aims to reduce time to treatment for heart attack patients in IMSS hospitals by improving communication through chat groups and capabilities by improving the admission process for incoming patients. I find that the program had a large effect on survival and transfers, but only among general hospitals who have a significant survival-rate gap to the more advanced reperfusion centers they can send transfers to. Such hospitals improve their survival rate 29% (11.7 pp), increase transfers 85% (5pp) and reduce transfer time by 30% (4 hours).

Through a structural model the paper interprets the reduced form results and explains that the pattern of higher effectiveness arises in hospitals with a larger skill-gap because the gain of transfer is higher for these hospitals. Moreover, by estimating the structural parameters the model presents counterfactual policy analysis and isolates the contribution of each component of the program. Results suggest that the communication channel alone would have gotten 68% of the total effect (8pp), highlighting the potential of leveraging widespread technologies. Moreover, the estimates suggest that the capabilities component alone would have gotten a comparable return of 64% of the effect (7.5pp). The fact that the effects of both components add up to over 130% suggests that they are substitutes. The main reason is that patients who are transferred cannot enjoy better service at the general hospital and patients who stay cannot get the benefits of better transfers.

Fragmentation is one of the most important challenges for health networks as the lack of coordination and efficient communication across physicians hinders their ability provide high quality and timely care. In this paper, I provide evidence of the large potential that ICT has for reducing fragmentation and improving health outcomes. Moreover, through the lens of a structural model, I find that ICT interventions have a higher potential when there is a large skill-gap between participants. Lastly, this paper highlights a more accessible way in which developing countries could start utilizing and benefiting from the potential of health information and communication technologies.

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Tables and Figures

Tables

Table 1: Implementation dates

Network	CI date
D.F. Sur / Morelos / Querétaro	Feb-15
Yucatán / Campeche	Oct-15
D.F. Norte, Estado de México Ote y Pte.	Nov-15
Jalisco / Nayarit	Feb-16
Sonora / Sinaloa	Apr-16
Nuevo León	Aug-16
Puebla / Tlaxcala	Sep-16
Baja California	Oct-16
Coahuila / Durango/Zacatecas	Oct-16
Tabasco, Veracruz Sur	Oct-16
Guanajuato/Aguascalientes	Oct-16
Veracruz	Nov-16
Colima, Jalisco	Jul-17
Hidalgo	Oct-17
San Luis Potosí	Oct-17
Michoacán	Feb-18
Chiapas	Feb-18
Baja California Sur	Mar-18
Chihuahua	Mar-18
Quintana Roo	Mar-18
Oaxaca	Apr-18
Tamaulipas/ Veracruz	Apr-18
Guerrero	May-18

Notes: This table presents the months and years at which each network started the CI program. We can see that there are 23 netwokrks who received it overall.

Table 2: Cases Descriptive Statistics

	All	Reperfusion Center	General Hospital	Non-Transferred	Transferred
Survival Rate	0.686	0.817	0.599	0.564	0.889
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)
Transfer Rate	0.0660		0.110		
	(0.001)		(0.001)		
GH Arrival	0.602				
	(0.002)				
Male	0.665	0.708	0.637	0.620	0.782
	(0.002)	(0.003)	(0.002)	(0.002)	(0.006)
Age	65.58	64.10	66.55	66.96	63.22
	(0.059)	(0.094)	(0.076)	(0.083)	(0.157)
Transfer Time					12.24*
					(0.194)
Observations	80534	32026	48508	43195	5313

Standard errors in parentheses

Notes: This table presents descriptive statitics for the heart attack cases. Summary statistics are presented for every case and restricting to patients who first arrived at a reperfusion center, a general hospital. Moreover, the latter is further split into patients who were transferred or not. *The transfer time mean is based on transfers that took under 48 hours.

Table 3: DID Results for D.F South

	Survival Rate (GH Arrivals)	Transfer Rate (GH Arrivals)	Transfer Time GH transfers	Survival Rate (RC Arrival)
	(3)	(4)	(5)	(2)
			0	
Tpost	**0.103****	**0.064****	**-0.278**	**-0.017**
	(0.041)	**(0.028)**	**(4.119)**	**(0.040)**
Obs.	2,412	2,412	136	1,223
R2	0.101	0.049	0.395	0.018
Pre-mean	0.538	0.108	10.24	0.870

Robust Standard errors in parenthesis
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table presents the results from the CI program on survival rate when arriving first to a general hospital urgent wing, the effect on transfers, the effect on hours it takes to execute a transfer whenever the transfer was under 48 hours and the survival rate effect when arriving first to a reperfusion center urgent wing, I control for expansion/hospital fixed effects, month fixed effects. Robust standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: DID Placebo Results for D.F South

	Survival Rate (GH Arrivals)	Transfer Rate (GH Arrivals)	Transfer time GH transfers	Survival Rate (RC Arrival)
	(3)	(4)	(5)	(2)
			0	
Tpost	**-0.027**	**0.012**	**3.893**	**0.036**
	(0.040)	**(0.024)**	**(3.772)**	**(0.046)**
Obs.	2,484	2,484	97	1,051
R2	0.101	0.049	0.395	0.018
Pre-mean	0.571	0.0879	9.079	0.805

Robust Standard errors in parenthesis
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table presents the placebo test when shifting the implementation date by 12 months. This table presents the results from the CI program on survival rate when arriving first to a general hospital urgent wing, the effect on transfers, the effect on hours it takes to execute a transfer whenever the transfer was under 48 hours and the survival rate effect when arriving first to a reperfusion center urgent wing, I control for expansion/hospital fixed effects, month fixed effects. Robust standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Stacked Cases Descriptive Statistics

	All	Reperfusion Center	General Hospital	Non-Transferred	Transferred
Survival Rate	0.664	0.748	0.612	0.592	0.880
	(0.002)	(0.003)	(0.002)	(0.003)	(0.006)
Transfer Rate			0.0689		
			(0.001)		
GH Arrival	0.617				
	(0.002)				
Male	0.650	0.676	0.633	0.623	0.778
	(0.002)	(0.003)	(0.002)	(0.002)	(0.008)
Age	65.46	64.31	66.17	66.46	62.31
	(0.062)	(0.114)	(0.071)	(0.074)	(0.220)
Transfer Time					14.76
					(0.287)
Observations	65786	25210	40576	37779	2797

Standard errors in parentheses

Notes: This table presents descriptive statitics for the heart attack cases. Summary statistics are presented for every case and restricting to patients who first arrived at a reperfusion center, a general hospital. Moreover, the latter is further split into patients who were transferred or not. *The transfer time mean is based on transfers that took under 48 hours.

Table 6: Program Effects

	Survival Rate (GH Arrivals)	Transfer Rate (GH Arrivals)	Transfer time GH transfers	Survival Rate (RC Arrival)
	(3)	(4)	(5)	(2)
Tpost	**0.037*****	**0.025****	**-4.135*****	**0.020**
	(0.014)	**(0.011)**	**(1.559)**	**(0.012)**
Obs.	40,561	40,561	1,382	25,210
R2	0.073	0.087	0.459	0.128
Pre-mean	0.577	0.106	12.54	0.874

Robust Standard errors in parenthesis
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table presents the results from the CI program on survival rate when arriving first to a general hospital urgent wing, the effect on transfers, the effect on hours it takes to execute a transfer whenever the transfer was under 48 hours and the survival rate effect when arriving first to a reperfusion center urgent wing. I control for expansion/hospital fixed effects, month fixed effects and cluster standard errors at the network/expansion level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Placebo Program Effects

	Survival Rate (GH Arrivals)	Transfer Rate (GH Arrivals)	Transfer time GH transfers	Survival Rate (RC Arrival)
	(3)	(4)	(5)	(2)
			0	
Tpost	**-0.027**	**0.012**	**3.893**	**0.036**
	(0.040)	**(0.024)**	**(3.772)**	**(0.046)**
Obs.	2,484	2,484	97	1,051
R2	0.101	0.049	0.395	0.018
Pre-mean	0.571	0.0879	9.079	0.805

Robust Standard errors in parenthesis
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table presents results when shifting start date of program by 12 months. The table presents the results from the CI program on survival rate when arriving first to a general hospital urgent wing, the effect on transfers, the effect on hours it takes to execute a transfer whenever the transfer was under 48 hours and the survival rate effect when arriving first to a reperfusion center urgent wing. I control for expansion/hospital fixed effects, month fixed effects and cluster standard errors at the network/expansion level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Skill-Gap and Distance Interactions

	Survival Rate (GH Arrivals)	Transfer Rate (GH Arrivals)	Survival Rate (GH Arrivals)	Transfer Rate (GH Arrivals)
	(1)	(2)	(3)	(4)
Tpost*Skill	**0.374***** **(0.106)**	**0.058**** **(0.027)**		
Tpost*Distance			**0.00001** **(0.00009)**	**-0.00010** **(0.00009)**
Observations	40,534	40,534	40,561	40,561
R-squared	0.074	0.087	0.07327	0.08722
Pre-CI mean dep var	0.577	0.106	0.577	0.106

Clustered by unit/expansion standard errors in parenthesis
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table presents the interaction coefficients when interacting Tpost with the skill-gap or distance following 1. I control for expansion/hospital fixed effects, month fixed effects and cluster standard errors at the network/expansion level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Skill-Gap Group Analysis

	Survival Rate (GH Arrivals)	Transfer Rate (GH Arrivals)	Transfer time (GH Arrivals)
	(1)	(2)	(2)
Tpost*Q1skill	**-0.019**	**0.022**	**-3.422***
	(0.032)	**(0.019)**	**(1.803)**
Tpost*Q2skill	**0.015**	**0.005**	**-4.545****
	(0.018)	**(0.012)**	**(2.083)**
Tpost*Q3skill	**0.117*****	**0.048*****	**-4.489**
	(0.034)	**(0.013)**	**(2.728)**
Observations	40,561	40,561	1,382
R-squared	0.074	0.087	0.459
Low mean	0.709	0.114	11.56
Medium mean	0.613	0.147	13.95
High mean	0.405	0.0569	10.94

Clustered by unit/expansion standard errors in parenthesis
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table presents the interaction coefficients when interacting Tpost with the skill-gap group. Classification is based on distribution terciles among the treated units. Specification is based on 1. I control for expansion/hospital fixed effects, month fixed effects and cluster standard errors at the network/expansion level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 10: Conditional Analysis

	Survival Rate (Stayers)	Survival Rate (Transferred)
	(1)	(2)
Tpost*Q1skill	**-0.026**	**0.020**
	(0.033)	**(0.047)**
Tpost*Q2skill	**0.019**	**0.038**
	(0.025)	**(0.041)**
Tpost*Q3skill	**0.100*** **	**0.038**
	(0.037)	**(0.055)**
Observations	37,764	2,581
R-squared	0.082	0.216
Low mean	0.686	0.899
Medium mean	0.562	0.907
High mean	0.376	0.893

Clustered by unit/expansion standard errors in parenthesis
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table presents the interaction coefficients when interacting Tpost with the skill-gap group. Classification is based on distribution terciles among the treated units. Specification is based on 1. I control for expansion/hospital fixed effects, month fixed effects and cluster standard errors at the network/expansion level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 11: Data Moments

Based on Reduced-Form Estimates			
Moments	Pre-CI	Effect	Post-CI
Survival GH-stay	0.4	0.09	0.49
Survival GH-transfer	0.89	0	0.89
Survival RC	0.87	0	0.87
Transfer-rate	0.06	0.05	0.11

Notes: This table presents the data moments that I utilize in the model estimation. I define the pre-CI moments as the mean from the data before the intervention for the treated units and shift those moments based on the reduced form estimates to define the post-intervention values.

Table 12: Machine Learning Predictions

	MSE
Logit	0.1978
Lasso	0.1972
Ridge	0.2005
Elnet	0.1973

Notes: This table presents the MSE obtained after training the data with different algorithms in 2014 to predict mortality and predicting out of sample for later years.

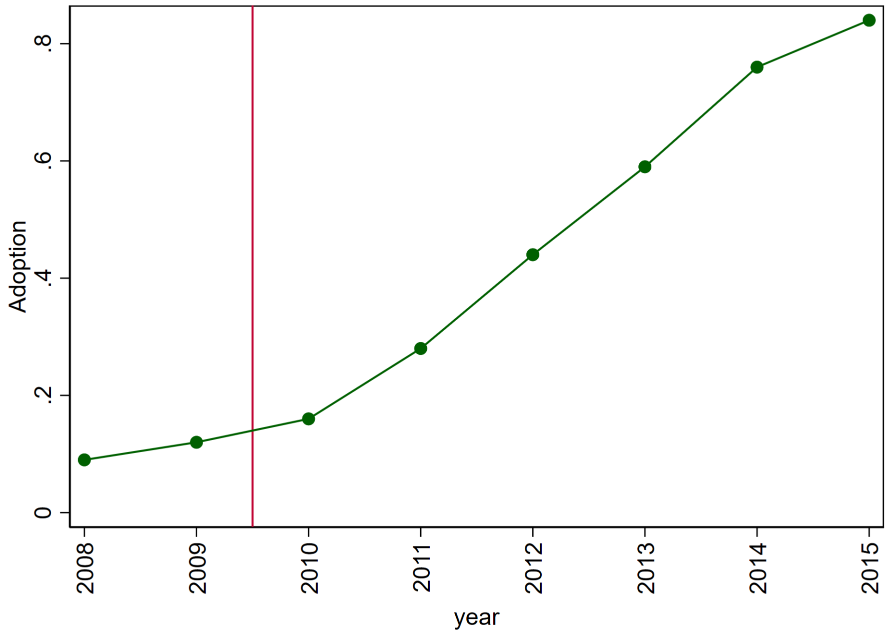
Table 13: Add caption

Parameters	Before	After
GH Capabilities λ_{GH}	1.8	2.2
	(0.05)	(0.07)
Transfer cost c	1.6	1
	(0.15)	(0.15)
RC Capabilities λ_{RC}	6.3	6.3
	(0.17)	(0.11)
Threshold κ	0.15	
	(0.033)	
α	5.6	
	(0.13)	

Notes: This table presents the structural parameters we obtain from adjusting the model and how they change after the CI implementation. Bootstrapped standard deviation reported in parenthesis from randomly taking 80% of the sample and re-estimating the data moments.

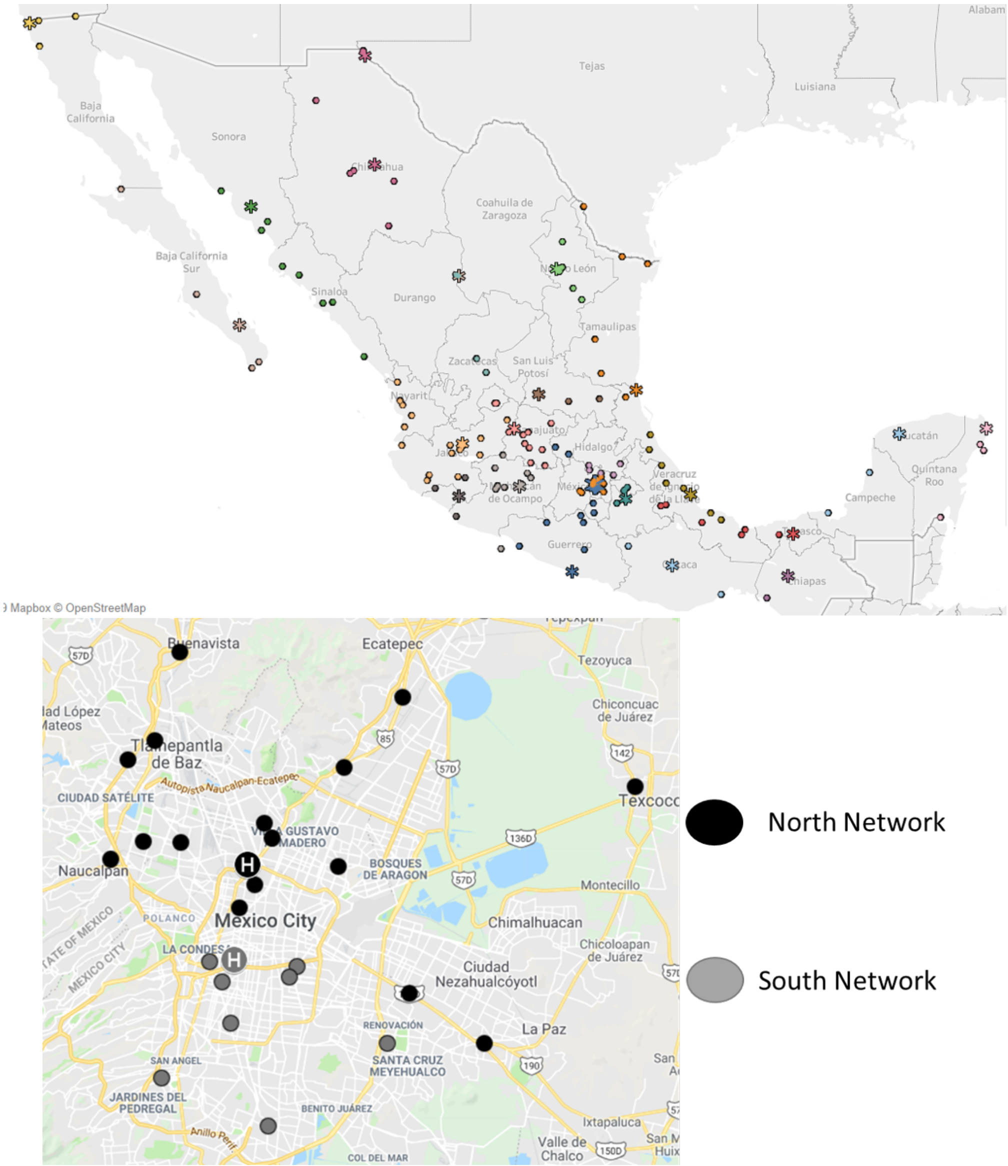
Figures

Figure 1: Electronic Health Records (EHR) Adoption



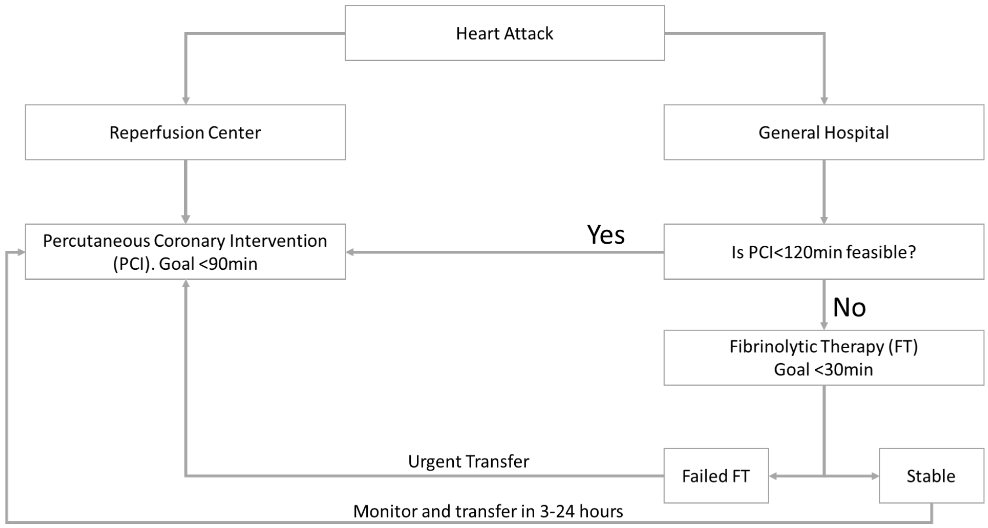
Notes: This figure presents estimates of the fraction of hospitals who were using "Basic EHR without clinician notes" in the year indicated. The points official estimates from the Office of the National Coordinator (ONC) of Health Information Technology (re-weighted to correct for nonrandom sample response). The vertical axis is set so that 1 = 100% (complete adoption).

Figure 2: IMSS' heaart attack networks



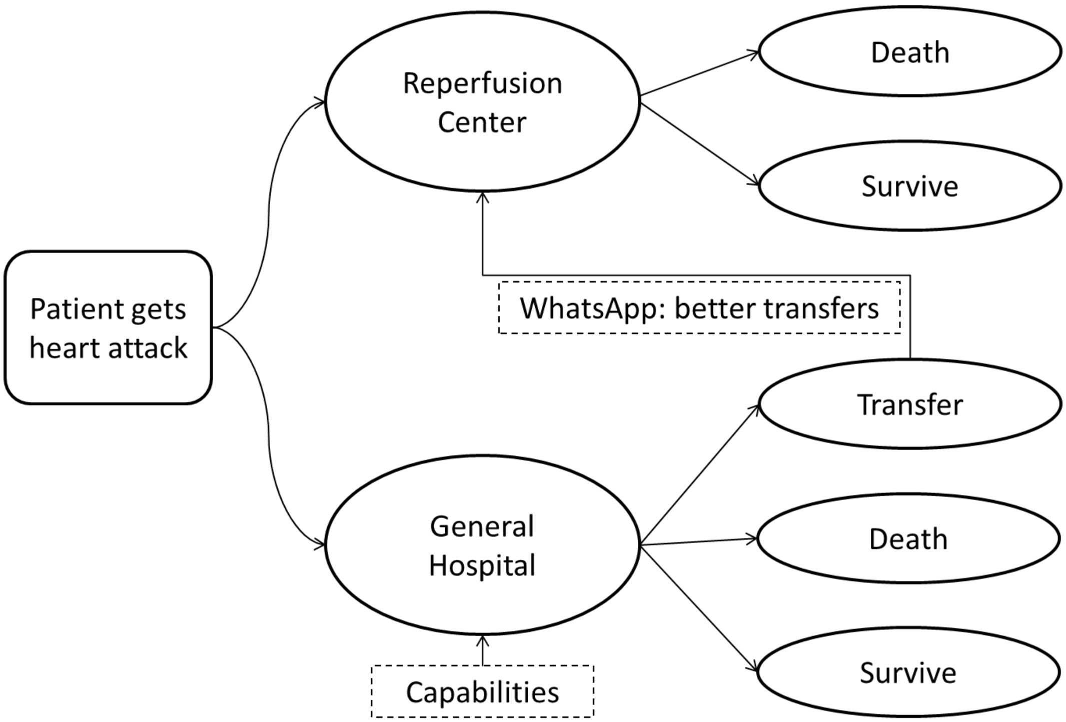
Notes: This figure presents the overall map of IMSS heart attack networks and a close up on the 2 networks that are in Mexico CIty.

Figure 3: Survival Function



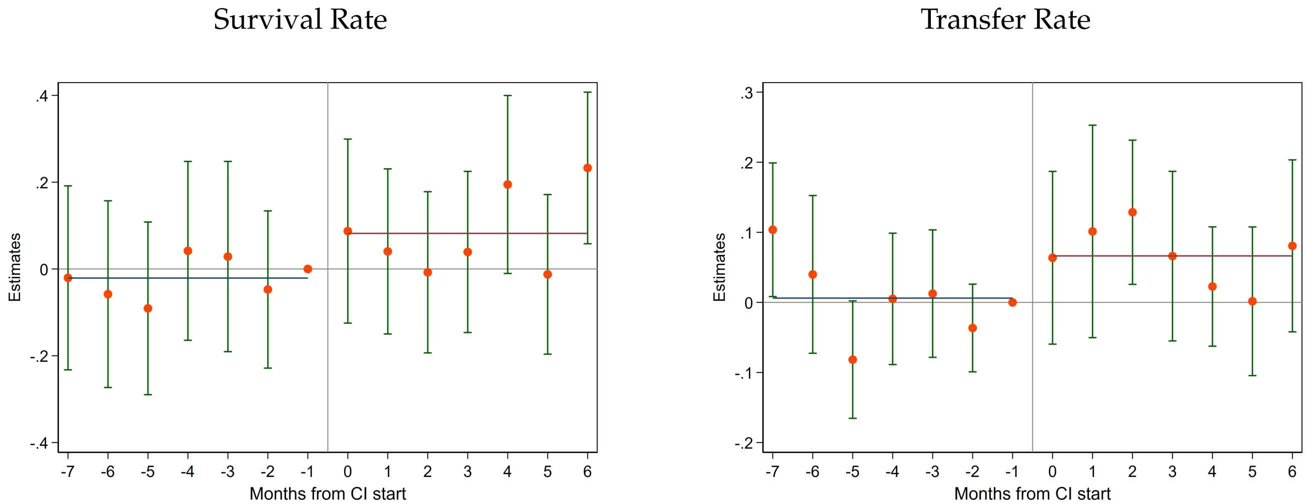
Notes: This figure summarizes the algorithm recommended by the ACCF/AHA guideline for the management of ST-elevation myocardial infarction: a report of the American College of Cardiology Foundation/American Heart Association Task Force on Practice Guidelines.

Figure 4: Código Infarto



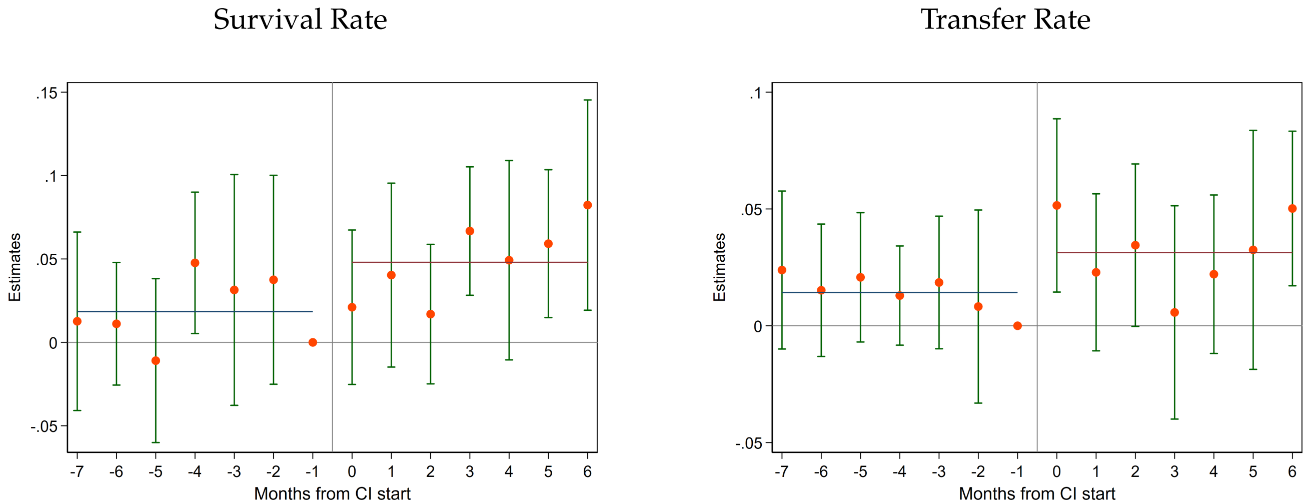
Notes: This figure represents the main changes that the CI program induced on the hospital networks' productivity. We can see that the program induced higher capabilities by the general hospitals, improved communication across GH and RC and could have potentially affected the Rc performance because of increased demand.

Figure 5: Event Studies for Mexico City



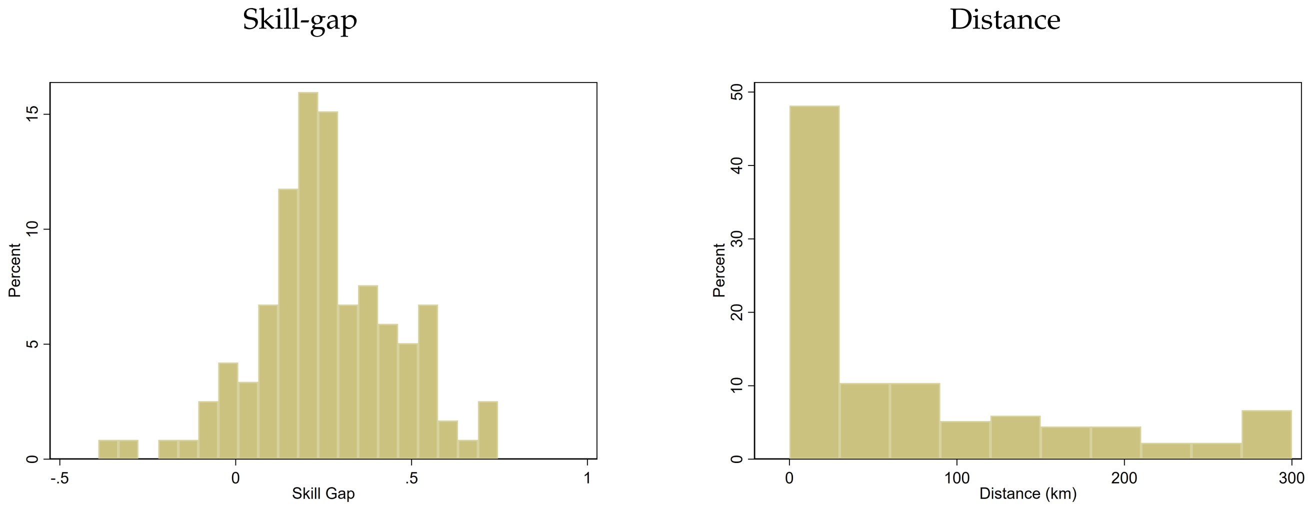
Notes: This figure presents the results from the CI program on survival rate when arriving first to a general hospital urgent wing and the effect on transfers. I control for expansion/hospital fixed effects, month fixed effects and relative time to starting the program. Standard errors are robust. 95% confidence intervals are reported.

Figure 6: Event Studies for Stacked Data



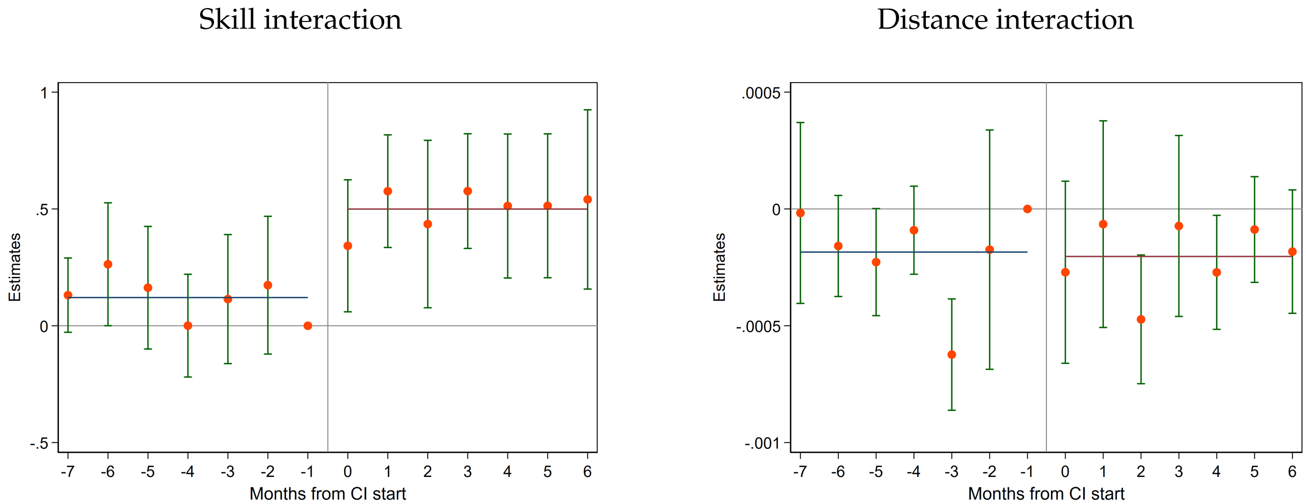
Notes: This figure presents the results from the CI program on survival rate when arriving first to a general hospital urgent wing and the effect on transfers. I control for expansion/hospital fixed effects, month fixed effects and relative time to starting the program. Moreover I cluster standard errors at the hospital/expansion level. 95% confidence intervals are reported.

Figure 7: skill-Gap and Distance Histograms



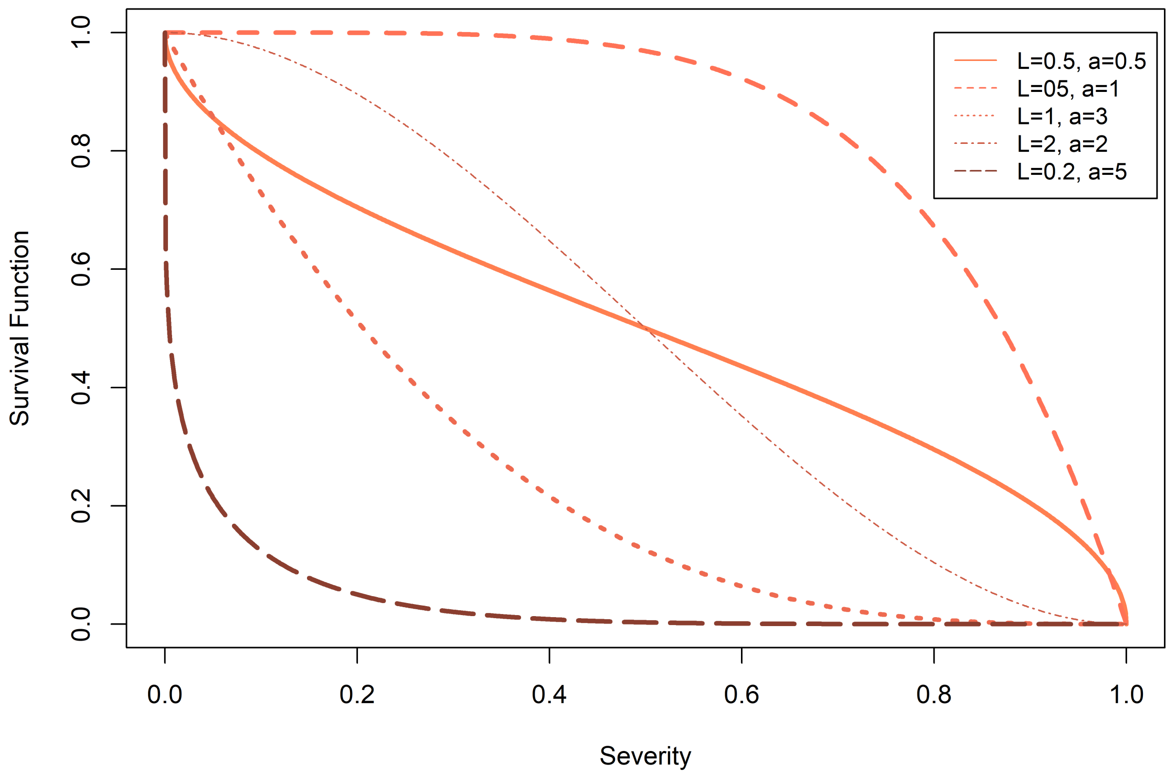
Notes: This figure presents the histograms from the distance in km between general hospitals and reperfusion centers and the skill gap defined as survival rate upon arrival between general hospitals and reperfusion centers

Figure 8: Event Studies for Interaction



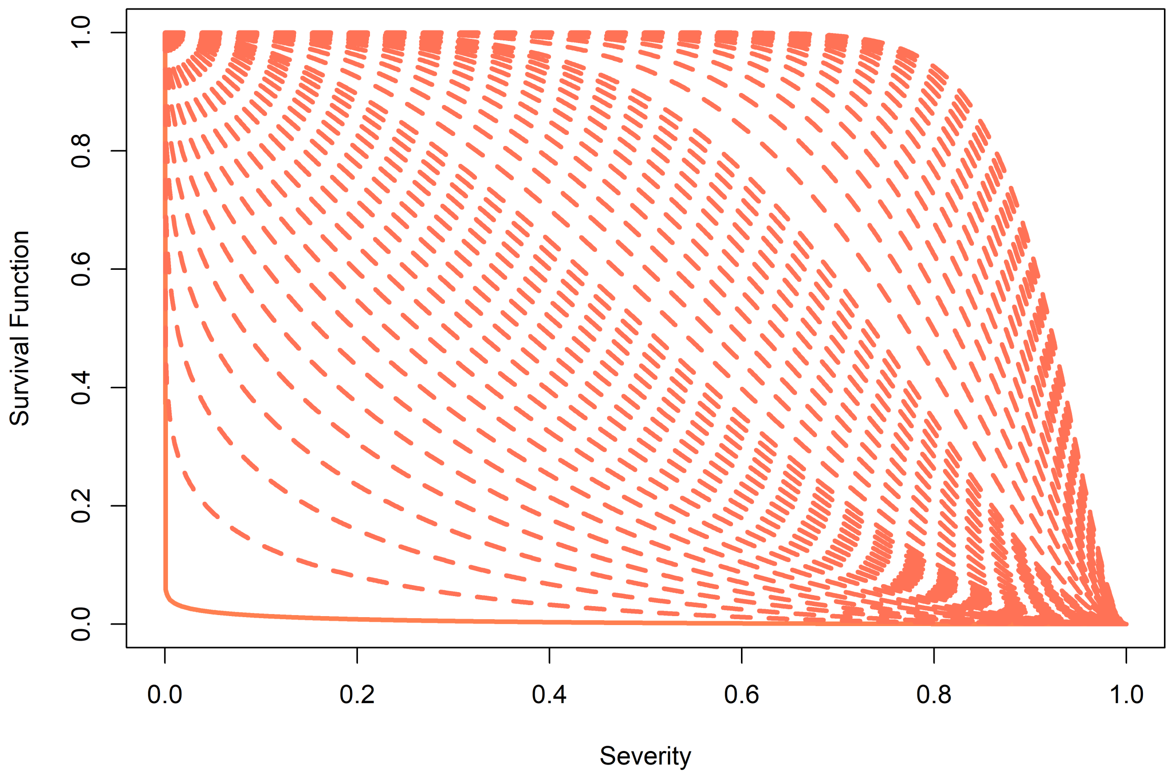
Notes: This table presents the interaction coefficients when interacting Tpost with the skill-gap or distance following 1. I control for expansion/hospital fixed effects, month fixed effects and cluster standard errors at the network/expansion level. 95% confidence intervals are reported.

Figure 9: Survival Function



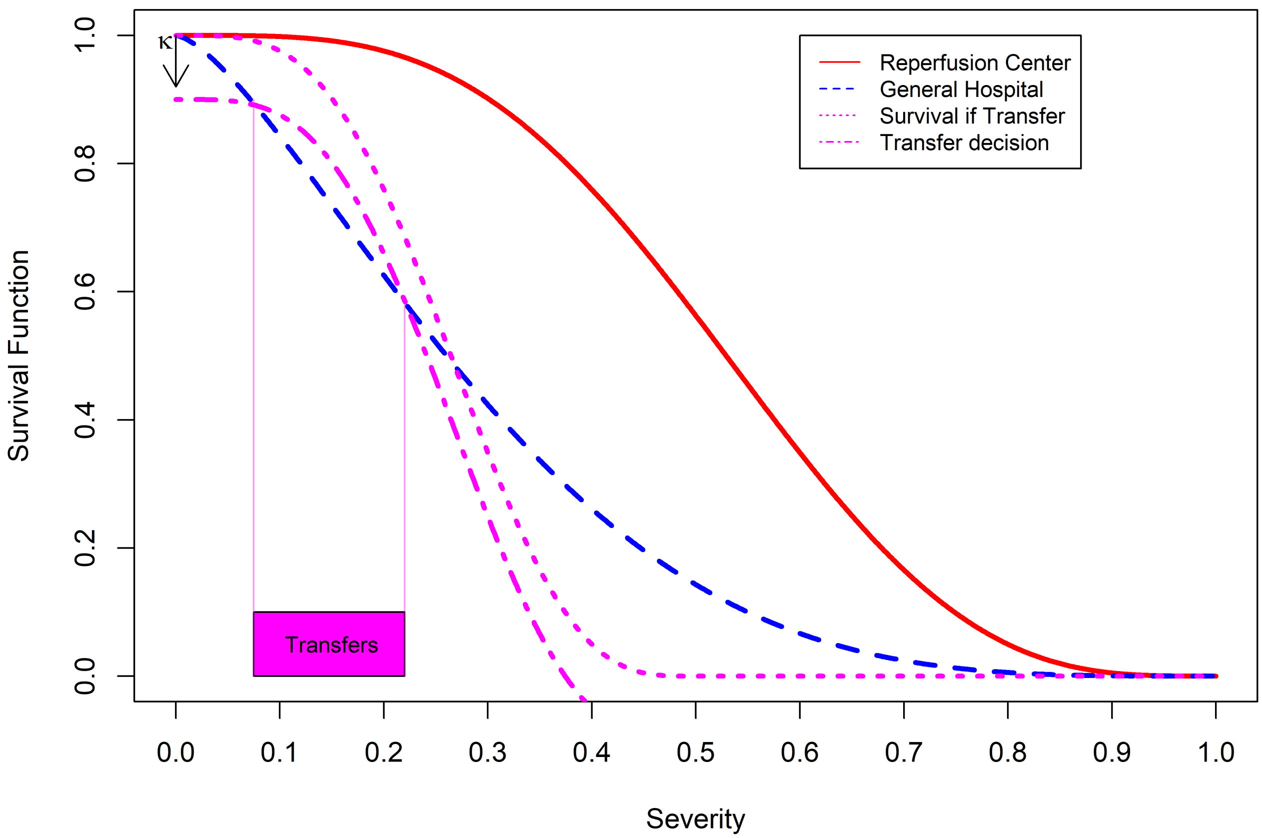
Notes: This figure represents the different functional shapes that the defined survival function can take.

Figure 10: Survival Function



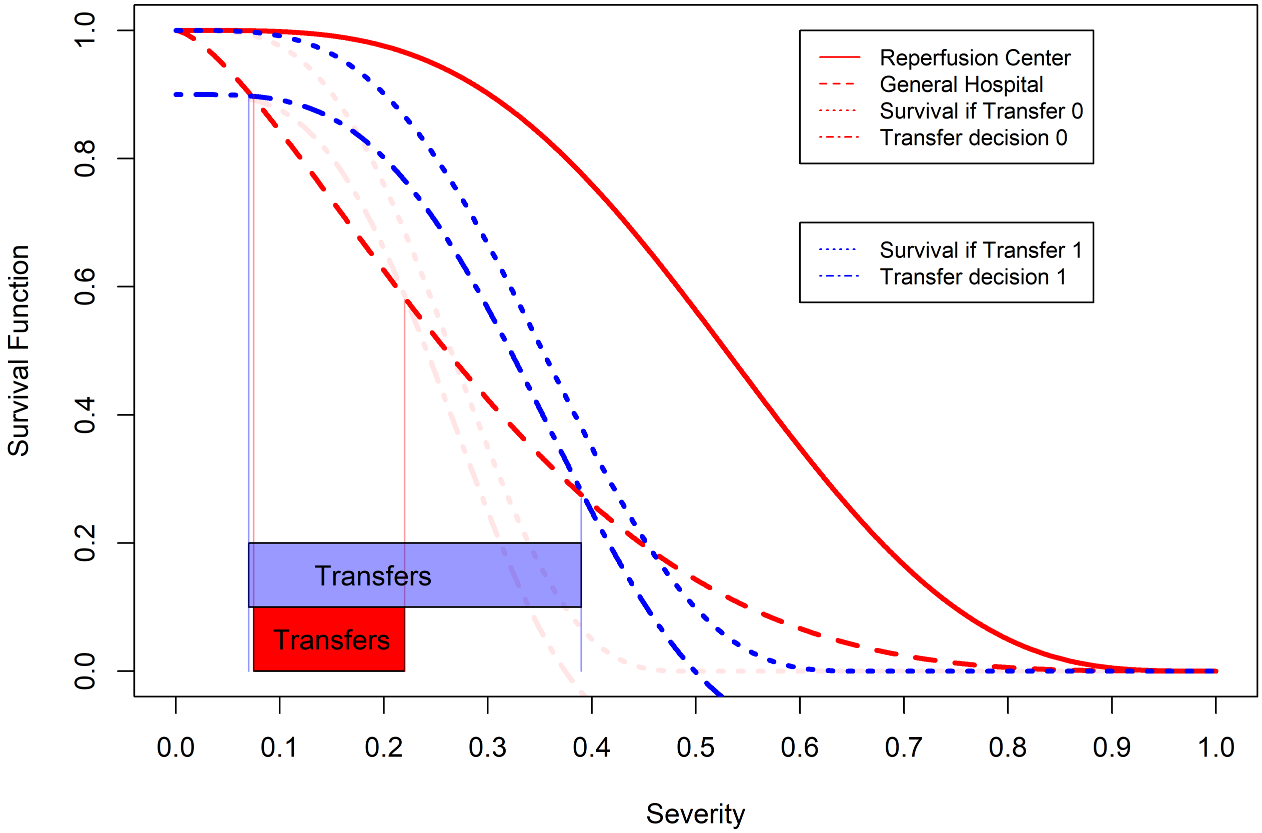
Notes: This figure presents how once α is fixed, a higher λ provides a better opportunity to live for every heart attack patient.

Figure 11: Transfer Decision



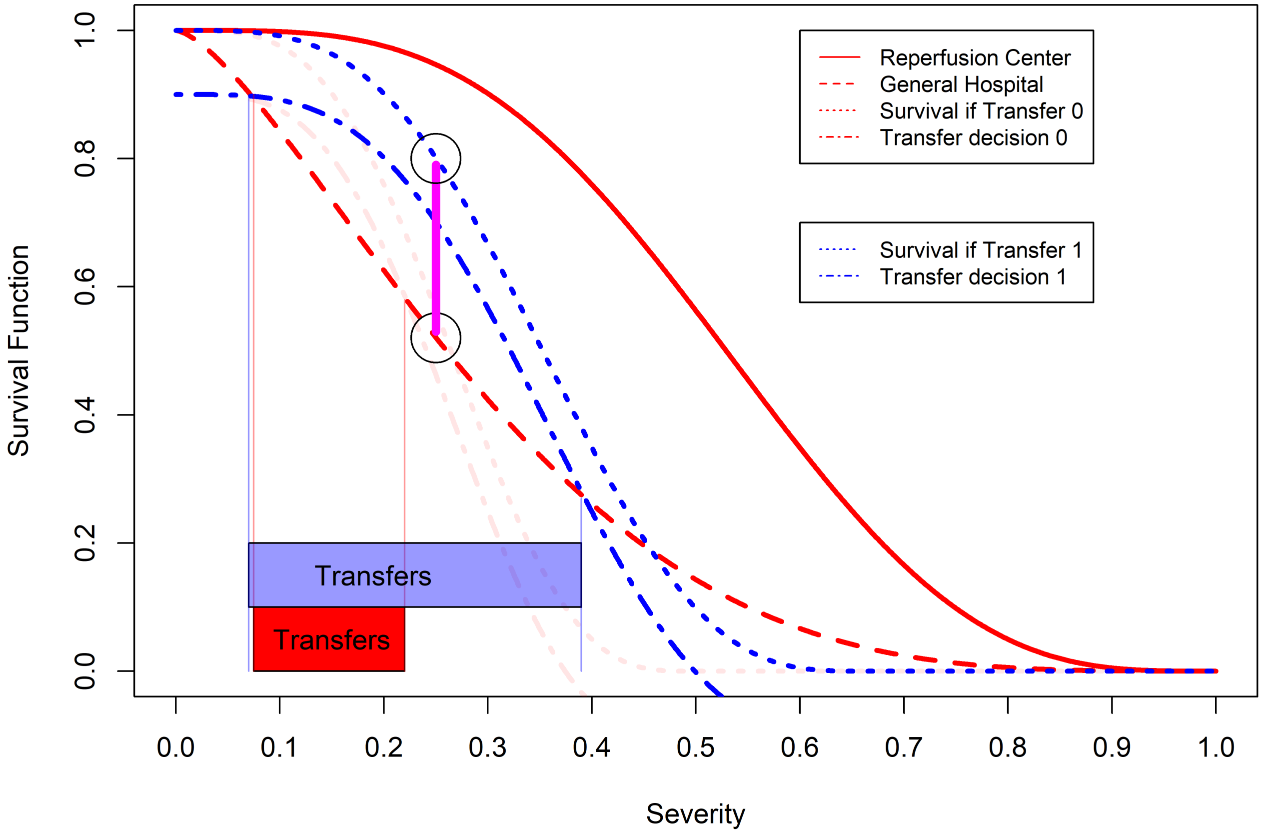
Notes: There are 4 lines in the image. The Blue line with long dashes captures the survival function for GH. The red line represents the survival function that RC face. It dominates the blue line since $\frac{\partial}{\partial \lambda_j} s(\delta_i, \lambda_j) > 0$. The purple dotted line reflects the survival probability that a patient would face after transfer: $S(\delta_i + c \cdot \delta_i, \lambda_{RC})$. We can see that this line is lower than the RC because of the cost that has to be paid for transfer. Moreover, the difference increases as severity δ_i increases, since more complicated patients experience a higher cost. The purple line with long dashes highlights the transfer decision curve. This line represents the survival probability after transfer but displaced by κ downwards. That means that whenever the transfer decision line is above the blue line, a transfer will be worth it. The purple rectangle highlights such patients.

Figure 12: Effect of Lower c



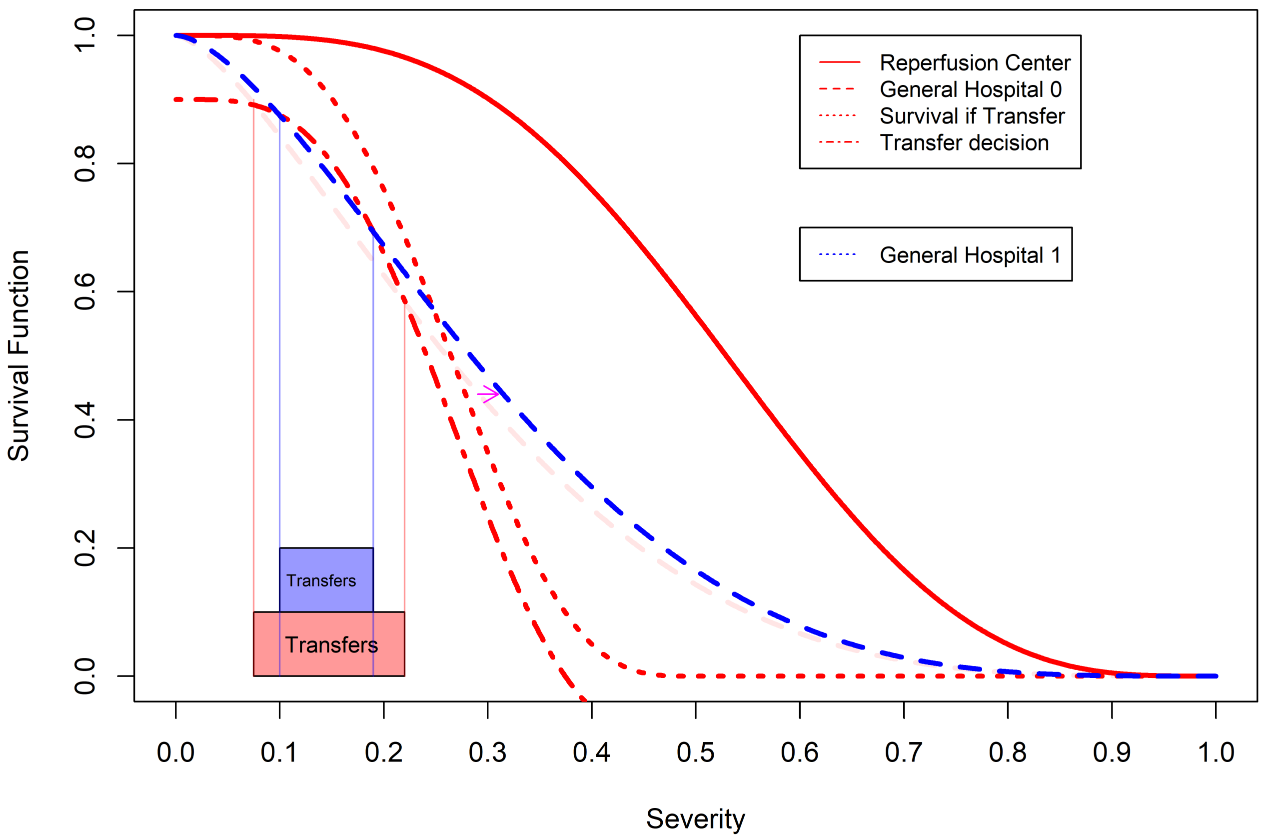
Notes: On the figure we can see the same 4 lines from 11 in red along with how the survival if transfer and transfer decision lines would look under a lower c. We can see that patients would now face a bigger survival probability after transfer, especially among more severe patients. This happens because the cost is increasing in terms of severity. We can see that there would be additional transfers and that those transfers would be focused on more severe cases as a consequence of this mechanism.

Figure 13: Effect of Lower c



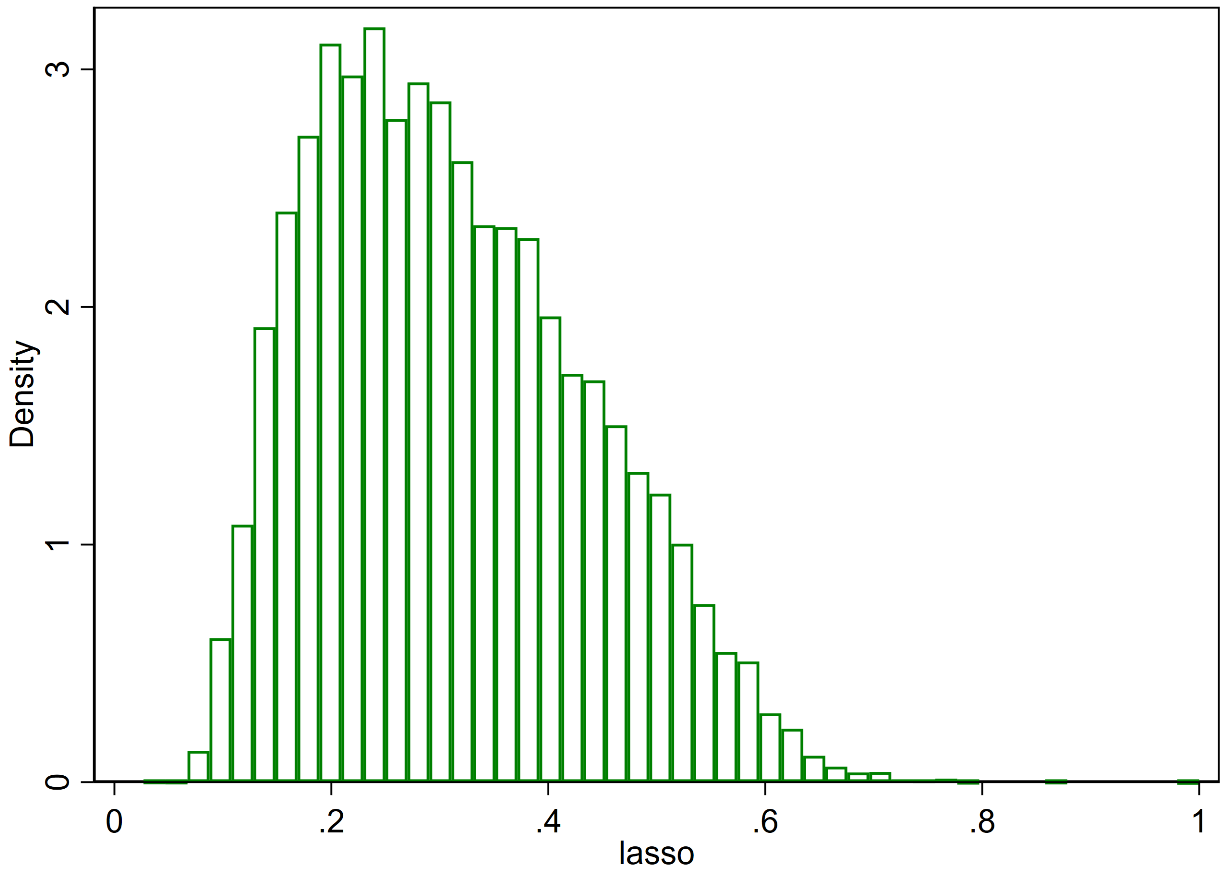
Notes: On the figure we can see the same 4 lines from 11 in red along with how the survival if transfer and transfer decision lines would look under a lower c. We can see that patients would now face a bigger survival probability after transfer, especially among more severe patients. This happens because the cost is increasing in terms of severity. The highlighted point shoes the benefits that one patient would get from the program.

Figure 14: Effect of Higher λ_{GH}



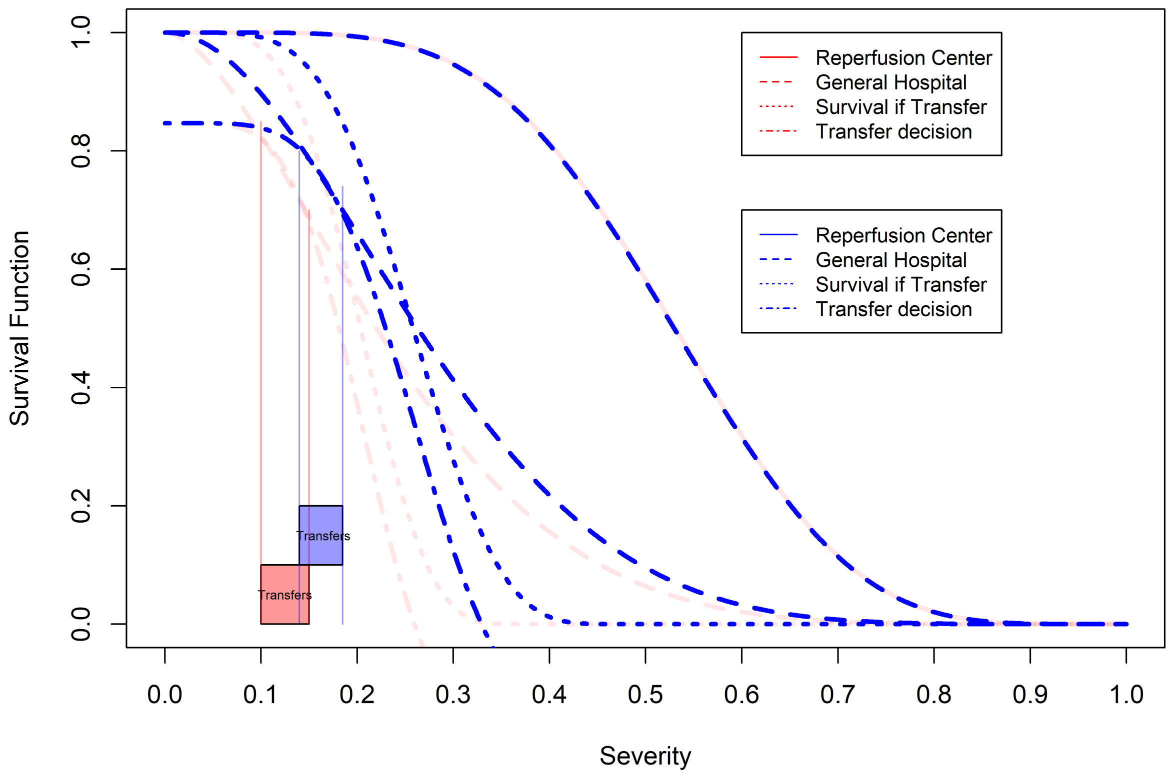
Notes: The figure highlights the same 4 lines from 11 in red along with how the shift in capabilities for general hospitals in blue. We can see that the shift induces a slight improvement for patients across severities and reduces transfers towards the middle. This pattern reflects that least and more severe patients who were just transferred no longer present a worthwhile investment in terms of health for the doctor.

Figure 15: Severity Estimation



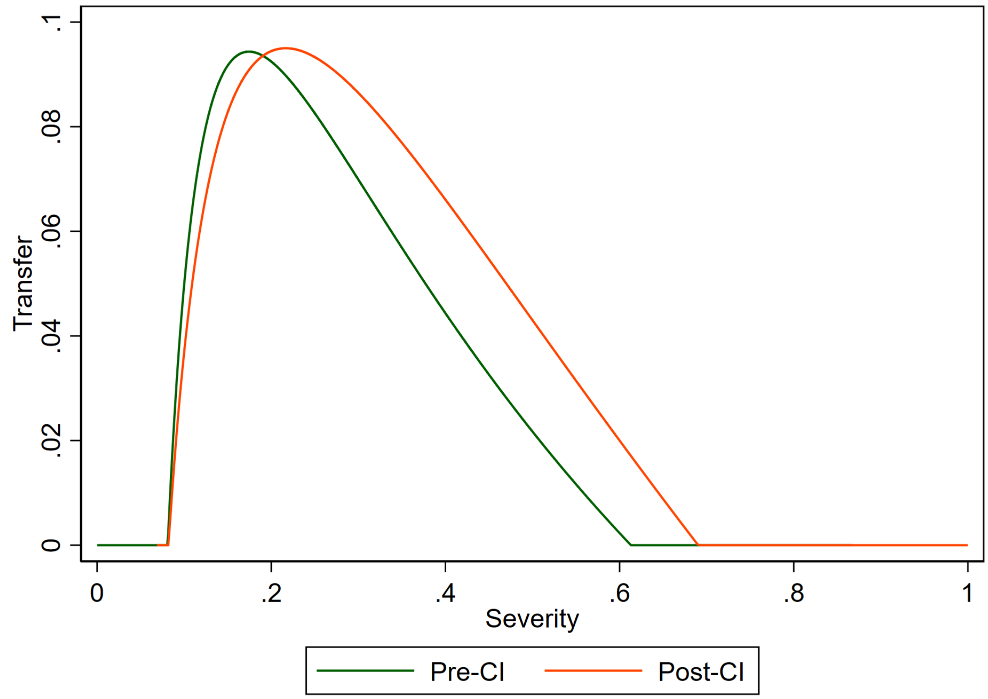
Notes: This figure presents the histogram of the estimated severity distribution that we have. This estimation was based on utilizing the year 2014 as the training data since no network had undergone the CI program and predicting for probability of death values for the rest. The data incorporates demographic factors from the patients along with hospitalization data from the 12 months before they had the heart attack.

Figure 16: Data in the Model Before and After CI



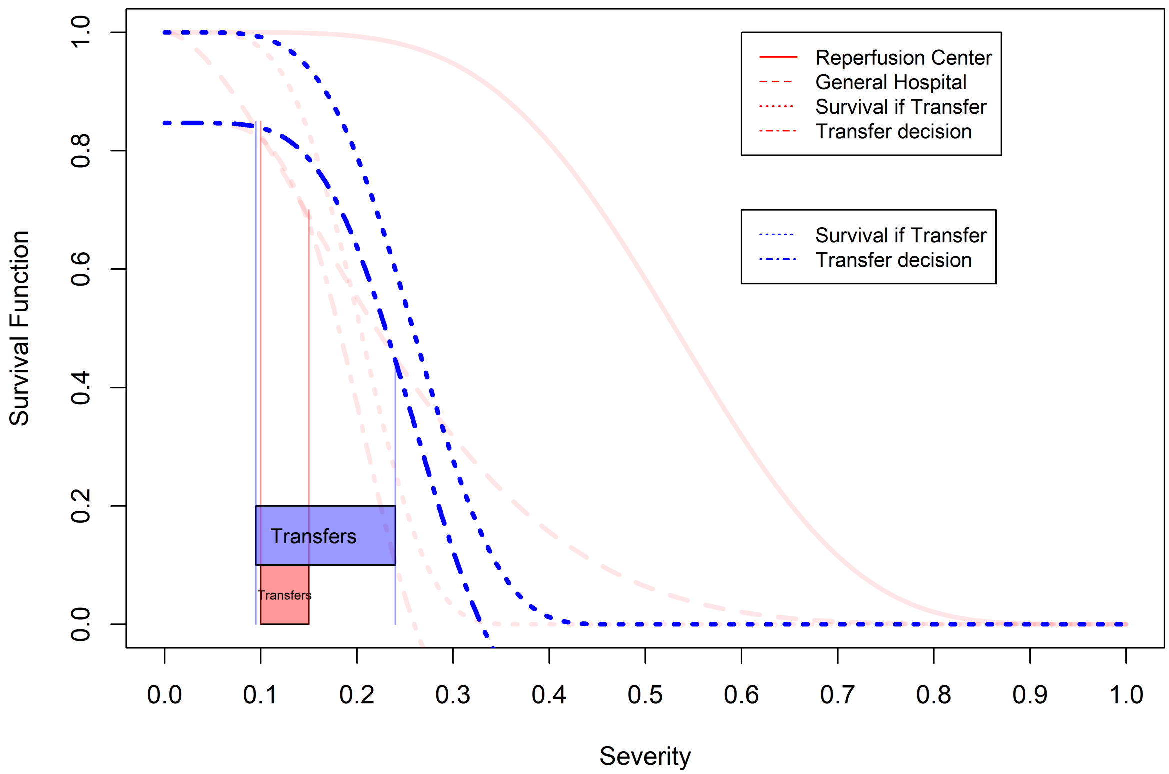
Notes: This figure presents how the estimated model looks before and after the CI program. The before estimations are shaded in the image. We can see that there is a big reduction in communication costs and a slight improvement in GH capabilities.

Figure 17: Transfers vs Estimated Severity



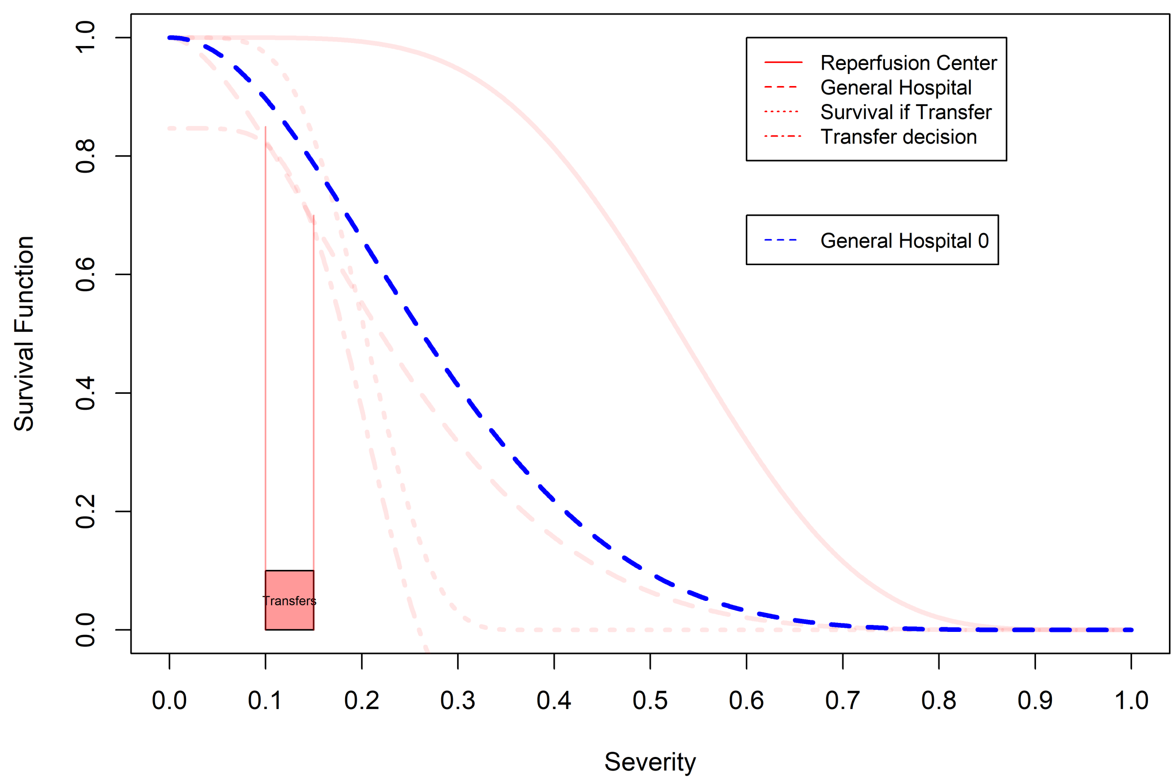
Notes: This figure represents the mean transfer rate observed in the data by estimated severity. Estimates were created using fractional polynomials

Figure 18: Data in the Model: Moving c



Notes: This figure presents how the estimated model looks before and after the CI program, when only incorporating the communication component. The before estimations are shaded in the image. We can see that there is a big reduction in communication costs and a big increase in transfers.

Figure 19: Data in the Model: Moving λ_{GH}



Notes: This figure presents how the estimated model looks before and after the CI program, but only incorporating the capabilities component. The before estimations are shaded in the image. We can see that after the program there would be an increase in survival but no more transfers.

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