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

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MIT

October 13, 2021

Abstract

Can widely available technologies 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) to reduce heart attack mortality by minimizing the 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 send patients to: survival rates increase by 29% (11 percentage points) and transfers by 85% (5 percentage points). I then present a model that disentangles the capabilities and communication channels and allows me to link the reduced-form results to structural parameters. A 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. Additional exercises highlight a degree of substitution between both components.

This paper is updated frequently. The latest version can be found here.

[*]I am immensely grateful to my advisors Jonathan Gruber, Joseph Doyle, John Van Reenen and Abhijit Banerjee for their enthusiasm and guidance. I thank David Autor, Amy Finkelstein, Ben Olken, Jim Poterba and Frank Schilbach for their useful comments on the project as well as participants in the development, organizational and PF lunches at MIT for useful questions and discussions. I am grateful to Kensuke Teshima and Hitoshi Shigeoka for their contributions on earlier stages of the project as well as Christian Norton and Kevin Schmidt for their collaboration. I am especially grateful to Dr. Gabriela Borrayo for her willingness and openness to discuss the Codigo Infarto in detail.

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1 Introduction

Radical improvements in information and communication technology (ICT) have been referred to as the "fourth industrial revolution" due to their potential to dramatically increase productivity and reshape the way we interact. Industries such as transportation, home entertainment, and food delivery have experienced dramatic changes and now rely on applications that automate and optimize service delivery.

Healthcare is one of the most exciting industries in which this technological revolution could have positive impacts. Healthcare delivery requires physicians to analyze information from multiple sources in order to properly diagnose and treat their patients. The doctor must be able to see the full picture to make the right decision. A lack of coordination and efficient communication across providers hinders medical professionals' ability to provide high-quality care by causing delays in treatment and increasing the risk of misdiagnosis and mistreatment, especially after transferring patients to different healthcare providers. The risk that such effects will be fatal increases if the patient has an acute condition that requires immediate attention or is receiving treatment for several specialists for a complicated illness. The failure to coordinate can be costly, as it often leads to double testing and over-prescribing.

In principle, ICT can help overcome most barriers to information sharing and coordination by automating reports and providing immediate access to a patient's medical history through electronic health records (EHR), which represent a substantial improvement over having to interpret another physician's illegible handwriting or imagining the results while talking on the phone. In a famous RAND study, (Hillestad et al., 2005) argue that the effective and widespread implementation of EHR could generate savings of over $81 billion per year in the U.S. while improving healthcare efficiency and safety. Several nations have recognized ICT's potential to improve healthcare efficiency and clinical outcomes, and have spent billions of dollars to develop centralized EHR systems capable of exchanging information.

For example, the US Health Information Technology for Economic and Clinical Health (HITECH) Act, passed in 2009 as part of the Affordable Care Act, allocated $30 billion to increase the take-up of EHRs, and the 21st Century Cures Act aims to regulate EHR systems to ensure that information is efficiently shared across systems. Figure 1 displays the evolution of hospital EHR adoption in the United States. It illustrates that prior to the HITECH Act, EHR adoption was less than 20% and has since increased dramatically to over 85%. Despite these large investments, however, overall the literature finds small positive effects of health information technology (IT) adoption; there is vast heterogeneity, and many adopters obtain no positive returns. A simple explanation for these results is that the systems do not communicate well across providers. A subsequent RAND study by (Kellermann and Jones, 2013) shows that the predicted effects of a shift to EHR did not materialize in part due to a lack of information sharing across providers.

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

The Mexican public healthcare system serves 83% of the country's population and is composed of several institutions. The largest is the Instituto Mexicano del Seguro Social (IMSS), which services over 70 million people with 1,522 primary care clinics, 256 secondary care, general, hospitals, and 36 tertiary (high-specialty) hospitals. IMSS services are organized into regions that combine all three levels of service to provide care for a certain area. Unless it is an emergency, patients are referred from their primary care clinic to the secondary care hospital, and onto a tertiary center if needed. [1]

Most care organizations rely on general physicians or hospitals to treat most cases, and specialized hospitals to treat only complicated cases. In principle, this is an 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 the various levels of provision – particularly for acute conditions that require an immediate transfer to a specialized hospital. Without effective communication, inefficient transfers between levels of care could result in unnecessary costs and even deaths.

Heart attacks are one example of a condition that requires specialist care. A heart attack can be treated by either 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 involves inflating a tiny balloon in the artery and inserting a stent to unblock it; it helps patients who have suffered a severe heart attack to survive. The latter procedure needs to be performed by a specialist and not every hospital can do so. Transfers are key, because if a patient requires PCI, every minute that passes increases the likelihood of death. Current American Heart Association (AHA) guidelines recommend performing this procedure less than 120 minutes after the first contact.

Heart attack treatment is a useful setting in which to examine fragmentation within a system, since poor coordination generates 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 the disparities in treatment would be small. (Rathod et al., 2020) document that the difference in survival between arriving with a heart attack at a PCI-capable hospital and others is less

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

than 1.5% in London; in IMSS hospitals in Mexico City, the gap is much wider: heart attack patients who come directly to a PCI-capable hospital have an 86% survival rate, while those who arrive at a non-PCI-capable hospital first have only a 54% chance of survival.

One reason for the low rate of transfer in Mexico is poor communication between general hospitals (GHs) and PCI-capable hospitals, which are often referred to as reperfusion centers (RCs). Before the program's implementation, to transfer a patient a doctor had to call the RC, talk to a secretary and explain the need to talk to a physician. Then they had to wait for that person to find someone to come to the phone and then make the case to transfer the patient. After getting transferred to the RC, the patient would then be assigned to the next available physician in the urgent wing. The urgent wing doctor would have to read through the notes made at the GH for the first time and would potentially order additional tests to assess the patient's status before treatment. (Scholz et al., 2018) estimates that every additional 10 minutes it takes to transfer a patient with cardiogenic shock increases their risk of death by more than 3 pp; this kind of fragmentation is therefore deadly.

In such a situation, policy makers have two options to improve outcomes: (1) enhancing communication to allow for more effective transfers across hospitals or (2) investing in the capabilities of secondary hospitals to allow them to treat more complicated patients. In 2015, the economist running IMSS, together with the head of the Cardiology Department at a RC in Mexico City, set up the "Código Infarto" (CI) program that aims to reduce the 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 created chat groups on common apps (mainly WhatsApp) to share patient information. These groups allowed doctors to send electrocardiogram (ECG) scans to other physicians and coordinate transfers much more quickly. The second channel involved a 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 they would be treated more quickly.

The program started in Mexico City's southern network and has since expanded to all 23 networks and the 191 specialized hospitals that treat heart attacks. In each network, a PCI-capable RC oversees GHs and can receive transferred patients from a GH who require PCI. To study the CI program's effect, I use detailed case-level data for 80,354 individuals who suffered heart attacks. The data contains each patient's hospital admission date, diagnosis, whether or not they were transferred, and their survival outcome. I label each case by the initial urgent wing they visited (either RC or GH). A patient who was transferred from a GH to an RC will still be labelled GH since she went there first.

I begin with a case study of Mexico City's experience, drawing on a natural control group of hospitals in Mexico City's northern network that did *not* participate in the program until later on. 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 on a different date for each network, I utilize a stacking procedure to prevent negative weighing and a difference-in-differences (DID) approach to estimate the effect of the intervention.

I find that the CI program led to a 7% (3.7pp) increase in the survival rate and a 25% (2.5pp) rise in transfers; transfers became 25% (2 hours) faster on average. This is an enormous increase in survival rates, which is almost 50% larger than the mean 2.6pp improvement in heart attack mortality in Organization for Economic Co-operation and Development countries from 2007 to 2017 (O.E.C.D, 2019). Moreover, I confirm that this effect is causal by showing that it is driven by hospitals that have a larger survival rate gap compared to their RC. Hospitals in the top tercile exhibit a 29% (12pp) increase in survival and an 85% (5pp) increase in transfers. These results demonstrate that the intervention worked best where there was more to gain from additional transfers.

While the above results show that the intervention is effective, we cannot draw conclusions about the mechanisms since calculating either of the program component's contributions 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 their ability to do so, which probably induced additional transfers of more complicated patients. Disentangling each component's contribution is key from a policy perspective, as replicating the communication component of the program is straightforward in other settings faced with similar barriers to coordination.

To identify each component's contribution, I develop a structural model in which physicians at hospitals with heterogeneous capabilities decide how to treat a heart attack patient. The model allows physicians to transfer patients to a more advanced hospital but at a cost in terms of health severity: patients become sicker from the increased time to treatment. Doctors choose to transfer a patient if the expected gain in their probability of survival is high enough to make the investment worthwhile. The model shows that reducing the transfer costs (by improving coordination) would increase transfers as well as survival rates among more complicated patients, and that enhancing capabilities would lead to fewer transfers.

I employ the reduced-form estimates to back out the model's structural parameters, which I use to perform a counterfactual policy analysis. I conclude that facilitating 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 for each other because patients who are transferred cannot experience the benefits of better service at the sending hospital.

To the best of my knowledge, this paper is the first to directly observe the role of technology adoption on coordination across hospitals, and is the first project to evaluate the effect of adopting ICT on health outcomes in a developing country. More generally, the study highlights the role that widespread and widely accessible technologies can play in improving healthcare, which is also important for developed countries, since some hospitals are exploring the use of apps to increase the speed of communication.[2]

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature. Section 3 describes the background of the IMSS system and the CI program. Section 4 discusses the data. Section 5 presents the results of the 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 concludes.

2 Literature Review

This paper contributes to at least five strands of the literature. The first assesses how fragmentation affects 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 health IT has the potential to save billions of dollars and improve healthcare is because IT systems are inoperable across providers. Could a lack of communication explain these bad outcomes? This project is the first to analyze how improving communication across hospitals can improve health outcomes.

Second, this paper adds to the vast literature on how ICT affects health outcomes by providing evidence of the high returns to simple technology improvements in a developing country. (Atasoy et al., 2019) provides an overview of why ICT should help improve health outcomes. While the medical literature finds mostly positive effects, the economics literature shows substantial heterogeneity across the variety of settings, technologies, and populations analyzed. For example, (Agha, 2014) shows, based on US Medicare data, that EHRs do not improve outcomes, but increase spending. However, (Miller and Tucker, 2011) demonstrate that using health IT reduces infant mortality. Moreover, (McCullough et al., 2016) illustrates that IT primarily helps patients with more complicated health complaints. (Parente and McCullough, 2009) examine three technologies—EHR, picture archiving, and communication systems—and find that only EHR clearly enhances patient safety, while (Athey and Stern, 2002) conclude that adopting ICT at emergency call centers in the US that links caller identification to a location

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

database increased the survival rate of heart attack patients. (Bronsoler et al., 2021) presents an in-depth review of the economics and medical literatures, which contains several meta reviews.

Third, the paper advances research on how better management practices affect patient outcomes. To the extent that the CI program can be regarded as a better management practice, I establish a direct causal link between better management quality and improved patient health outcomes. While my paper is the first to directly link management practices to health outcomes, several previous studies have highlighted that management practices can improve productivity (for a review, see (Bloom and Van-Reenen, 2011)). Health IT is particularly important because healthcare staff are often resistant to change and fail to implement new technologies (review in (Gnanlet et al., 2019)). The current paper highlights that implementing health IT initiatives based on widely used technology could avoid the buy-in problem.

Fourth, this paper contributes to the literature on the 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-scoring hospitals receive patients with more severe conditions. Likewise, (Bloom et al., 2013) conclude that hospital competition leads to better hospital management and improved 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) argues that hospitals that are better at intensive treatment can more successfully treat individuals in need of such attention. We analyze one implication of such heterogeneity via the impact of ICT: does changing patients' hospital allocation affect patient outcomes?

Lastly, to the best of my knowledge, this paper is the first to conduct an in-depth analysis of the effect of a program such as CI. Several medical studies have examined 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)), while others have evaluated similar programs through pre-post strategies, including an evaluation of the CI program ((Gómez-Hospital et al., 2012), (Cordero et al., 2016), (Borrayo-Sánchez et al., 2017)). However, none of these studies offers a causal estimation of the effect, a description of the mechanisms through which the program operates, or an explanation of 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 IMSS, the single-payer insurance plan for the country's formal sector workers, their families, and students as well as a voluntary enrollment option that comprises fewer than 1% of the plan's beneficiaries. Private employers are required to enrol all employees in IMSS. This service is paid for in three parts: the government contributes 5.3% of employees' base wages, employers contribute 16.5%, and employees another 2.5%.[3] IMSS runs its own 1,522 primary care clinics, 256 general care hospitals, and 36 specialized hospitals. There are smaller but similar public options for particular sectors such as government workers (ISSSTE), the navy (SEMAR), the army (SEDENA), and well as employees of the state-owned oil company (PEMEX).[4]

IMSS has over 70 million beneficiaries. Its medical networks are organized into three levels. Primary care clinics treat regular illnesses that do not require complicated surgery, general (low-specialty) hospitals treat almost all illnesses and provide surgery services for beneficiaries, and high-specialty hospitals are equipped with cutting-edge technologies to treat the most complicated cases. Each IMSS beneficiary is assigned to a primary care clinic based on where they live. Each clinic is then ascribed to a GH, which in turn is assigned to a specialized tertiary unit. IMSS' heart attack treatment structure is organized into 23 networks; each has several GHs and one RC hospital to which severe patients can be transferred for advanced procedures. Figure 2 maps the location of each of IMSS network and provides a close-up of Mexico City's two networks.

A heart attack occurs when the flow of blood to the heart is blocked. The blockage is most often caused by a buildup of fat, cholesterol, and other substances that form a plaque in the arteries that feed the heart (coronary arteries). When the plaque ruptures, it can form a clot that blocks the blood flow, causing a heart attack. The interrupted flow deprives the heart of oxygen, which causes it to start dying. Heart attack patients must be promptly treated at a hospital with either FT or PCI. The 2013 AHA guidelines suggest a maximum of 30 minutes door to needle (FT) and 90 minutes door to balloon (PCI), or 120 minutes if a transfer is required. Thus heart attack patients should be transferred to a PCI-enabled hospital in less than 120 minutes or, if that is not feasible, FT should be administered within the first 30 minutes to stabilize the patient, and a potential transfer should be evaluated over the next 24 hours (O'gara et al., 2013). Figure 3 summarizes the algorithm. Receiving treatment quickly has a significant impact on survival rates: (Scholz et al., 2018) estimates a 3pp increase in the likelihood of death for every additional 10 minutes that a patient with cardiogenic shock takes to get to the RC.

The CI program aims to reduce the time between a patient's admission and treatment being provided, ultimately reaching the timeline proposed in the AHA guidelines. To achieve these goals, CI comprises two simple interventions. First, across hospitals, the program created chat groups between doctors at GHs and RCs so they can communicate efficiently about patient cases, prepare for incoming

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

heart attack patients, and coordinate transfers more effectively—a very inexpensive intervention. Second, within hospitals, the program improves the emergency procedures in 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 the main heart attack symptoms to all staff (security, cleaning, etc.) and instructing everyone to help incoming individuals with potential heart attacks receive treatment quickly. Figure 4 describes the improvements generated by the CI program.

Thus the CI program improves medical attention through two components. First, it improves hospitals' ability to treat heart attacks by prioritizing attention to heart attack patients during the triage and training all staff members to recognize the symptoms. Second, the program uses ICT to increase the flexibility and efficiency of transfers from non-PCI-capable hospitals to PCI-capable hospitals.

CI was first launched in February 2015 in Mexico City's southern medical network as a pilot program for its eight second-level hospitals and one PCI-capable hospital. After encouraging observations from the pilot network, by Summer 2018 the program had expanded to all 23 networks. A PCI-capable hospital (reperfusion center (RC)) in each network oversees general hospitals (GH) and receives transfers. The program is now running in 191 hospitals across the country. Table 1 lists the implementation dates 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 from the institute, I am able to track the full case of every heart attack patient who presented at an IMSS urgent wing between January 2013 and December 2019, the study's target population. A key advantage of IMSS' systems is that they all rely on a social security number combined with an intra-family ID to identify each individual, which allows them to identify and match patients across datasets. This allows me to obtain all the medical information from patients who were diagnosed with a heart attack in the urgent wing, including their hospitalization history and their survival outcome, even after leaving the hospital.

The first source of information is the urgent wing administrative data for 95,447 heart attack patients[5] who went to an IMSS urgent wing. This dataset 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 within 10 days of their admission. I define a case length as 30 days from the patient's first appearance in the urgent wing. Since patients usually present at the urgent wing of the receiving hospital after transfers, some cases appear more than once. After cleaning for double entries I have 80,539 cases.

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

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

To combine both datasets I conduct a many-to-one match from the urgent wing data into the hospital data and define an appearance as relevant if the date of entry is less than 30 days from the individual's first appearance in the urgent wing. I then define an individual as transferred if they appear at an RC (hospital or urgent wing) after starting in a GH, and consider a patient as surviving if they did not die within 30 days of the case starting. I identify 5,313 (7%) patients who were transferred, 70% of whom appeared in the urgent wing data in the receiving hospitals.[6] There were 21,769 deaths (27%), 91% of which appear in the urgent wing data. The last step to complement the death dummy variable is to incorporate the death census data from IMSS, which captures 3,640 additional out-of-hospital deaths (17% of the total).Results are robust to not including these deaths and defining different case lengths.

These three data sets allow me to observe the entire history of each heart attack patient who arrived at an IMSS urgent wing and estimate the program's effect. One limitation of the study is that I do not have detailed data on each patient's heart attack characteristics. That is, I cannot determine the severity of each case directly. Table 2 presents descriptive statistics of the data. The average survival rate is 68% (82% for those who came directly to RCs and 60% for those who first came to GHs). An average of 11% of patients were transferred, which takes 12 hours to execute. 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 employed to analyze the effects of the program and the results obtained. Since the CI was implemented in a staggered fashion, utilizing a simple two-way fixed effects model could lead to bias due to potential negative weighting. This is because if there are 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 used to evaluate the program as a whole, I first describe a simple DID design using Mexico City's networks as a motivating

[6]Some cases were not registered because the patient was directly admitted after their transfer.

example.

Mexico City, because of its size, has two full networks: South and North. As mentioned above, the CI program was first implemented in the city's South network in February 2015 and then gradually expanded to the remaining 22. The two RCs in Mexico (Siglo XXI and La Raza) are the largest medical centers in the IMSS network and compete to be the best hospital in the country; they have 87% and 85% heart attack survival rates, respectively.The program was launched in the South because it was designed by the cardiology chair in that areas at the time. D.F North started the program in early October but preparations were underway in the previous month, so I utilize data from the 3,654 heart attack cases between July 2014 and August 2015 in these two networks to evaluate the program within Mexico City, using 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 at time t.
- α_h are hospital fixed effects.
- γ_t are month fixed effects.
- $T_h$is a dummy indicating whether the hospital is in the South network.
- $Post_t$ is a dummy that denotes if the case started on or after February 2015.

Table 3 reports the results. It demonstrates that the program generated a 10 pp (20%) increase in survival rate for patients who first presented at a GH. There was also a 6.5 pp (60%) increase in the transfer rate, but no evidence of a reduction in transfer times (although the analysis is underpowered for this exercise). Lastly, the findings show that the program had no negative effect on patients who came directly to the RC. This was a big concern of the program's designers, as increased demand could have induced a negative externality. Figure 5 illustrates the event studies for survival rates and transfers. Table 4 validates the strategy by showing null results when conducting a placebo test in which I shift the implementation date to 12 months earlier.

Analyzing the full program has several advantages. First, it enables us to assess whether the program's effects are the same across hospitals and networks, and provides enough power to look for heterogeneous patterns and understand the potential mechanisms behind them. To do this, I employ a stacking procedure that eliminates the potential risk of negative weighting under two way fixed effect estimation, following (Deshpande and Li, 2019). The goal is to create a dataset that encompasses all treatments on the same timeline and thus eliminates the possibility of incorporating dynamic effects into the treatment/control comparisons.

I first create a unique dataset for each treatment starting time and normalize the treatment time for both the control and treatment groups around the start of the intervention. Each dataset includes only viable control groups (i.e., they are not affected by treatment dynamics since they have not been treated yet). I include only eventual adopters, as is standard in the literature. I then stack these datasets 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). I create 23 separate datasets and include as viable controls heart attack patients who will be treated but will not participate in the CI program during the next 8 months. My analysis focuses on the period 7 months before the intervention and 6 months after, following the Mexico City DID analysis presented above.[7]

The final stacked dataset contains data on 68,007 heart attack patients and 15 networks as treated groups. [8]. Table 5 reports the descriptive statistics of the new dataset. Overall, the results demonstrate that heart attack cases are similar to those described in Table 2: 13% of patients are transferred, and the overall survival rate is 66% (62% for GHs and 75% for RCs). Lastly, individuals are 65 years old on average and 65% are male.

I utilize the following specification to analyze the intervention:

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

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 indicating when $D^{\tau}_{e,t} \geq 0$

[7]Varying this time selection does not affect the results.
[8]The last networks to adopt have no viable control group

And the event study equivalent:

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

Table 6 reports the results. It shows that the program had a substantial effect on survival rates (3.7pp or 7%, on average) and generated a 2.5pp (24%) increase in transfers. Using a model with increased 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 the transfer time by 33%. Lastly, we see that there is no negative externality on the RCs; in fact, the estimate is positive. Figure 6 displays the event study estimates for this exercise, and there are no pre-trends. Moreover, Table 7 presents a placebo exercise that shifts the start date of the program by 12 months for each network and obtains null results.

Understanding whether the program's effect is constant across hospitals or whether it works better under certain conditions is relevant from a policy perspective, especially when considering the implementation of a similar policy. Likewise, policy makers would need to understand whether the program's impressive effects are driven by the simple communication component or by the more involved improvement in capabilities. Therefore in the next section I analyze heterogeneity, and then disentangle each component's contribution.

5.2 Heterogeneity

There are two sources of heterogeneity that may be driving hospitals' varying responses to the program. The first, is whether there is much to gain from transferring a patient. If a GH is almost as good at treating patients as its RC, or if its RC will not provide a timely PCI, then there may be little to gain from improving communication and coordination. The second possible source of heterogeneity is the distance from a GH to an RC, which could matter quite a lot since a transfer from farther away would take longer.

To assess whether the difference in capabilities between the types of hospitals plays a role, I define productivity as the pre-CI mean survival rate for patients who arrive at each hospital, and define a productivity gap as the difference between the skill at a GH vs. that of its RC before the treatment. I use the geographic coordinates for each IMSS clinic to calculate the distance from every GH to its RC.[9]. Figure 7 reports the histograms for both measures, which reveals significant variation. The median GH faces a 10% productivity gap and its RC is 80 km away.

To empirically test whether each of these components matters, I run a DID specification similar to equation 1 but include an interaction term between Tpost and the mechanism being explored. Table

[9]Time of transportation yields similar results

8 reports the results, which illustrate that there is a clear and strong correlation between skill gap and the size of the effect: GHs with a greater skill gap experience a larger effect. Moreover, the effect is not correlated with distance, suggesting that this is not a key driver of heterogeneity. Figure 8 reports the event studies for both interaction terms, and this pattern is even more apparent.

To further understand which hospitals are driving the effect, I classify treated hospitals into three categories based on productivity gap terciles (low, medium, and high) and replicate the analysis including interactions between Tpost and each of the categories. Table 9 reports the findings, which reveal an even larger effect among hospitals with a large skill gap but no effect among the rest of them. Hospitals with a large skill gap exhibit a 12pp (29%) increase in survival rates and a 5pp (86%) rise in transfers. Interestingly, we do find an effect on transfer times for every hospital.

To separate the contribution of each component we must account for the program's effect on transfer selection. On the one hand, when a GH becomes more capable, it does not need to transfer as many patients, which will lead to fewer transfers. On the other hand, transfers become easier when communication costs are lowered. One would expect that in this scenario there would be more transfers, and that the transferred patients would be more severe than before. The fact that the capabilities component would probably lead to a decrease in transfers and we observe an increase signals that the across component is playing a role. Moreover, we see direct evidence of its effect in shorter transfer times. Lastly, hospitals that have a larger survival rate gap compared to their RC experience a larger effect, suggesting that the program's effect is larger where there is more to gain from transfers.

To properly disentangle these components, below I develop a structural model in which doctors need to choose whether to transfer a patient for treatment that accounts for the cost of transfers in terms of health. Such a model is necessary because conditioning by transfer status does not incorporate selection: GH survival rates might be artificially improving by sending away more complicated patients. In fact, as shown in Table 10, when analyzing the effect of the program conditioning by whether the patient was transferred or not, we see a large increase in survival rate among patients who were not transferred. Additionally, we see no effect on survival for transferred patients, which could be hiding the fact that more complicated patients are now being transferred.

6 Mechanisms

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

Cheaper communication leads to more transfers, and there are two ways in which a rise in transfers can increase the survival rate for heart attack patients who first come to GHs: (1) by reducing overcrowded urgent wings and thus allowing doctors to be more focused on each patient and (2) by allowing patients to receive more specialized treatment in the RC faster. The latter affects patients selected for transfers, as lower costs mean that more severe cases can make the trip. I can empirically discard the former, as out of the 65,000 cases in GHs in the final sample, 54% were the only heart attack case a low-specialty urgent wing had that day. Further, only 9% arrived within less than 4 hours since the previous patient, and 5% within less than 2 hours. This is not to say that resources are not limited for such patients; it simply shows that the increase in transfers is unlikely to have played a role in the overall results through increased resource availability. 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 patients with complex needs. However, as shown above, the program has no negative effects on patients who arrive directly to an RC.

When all staff members are trained to react and heart attack patients are given top priority within the urgent wing, this is bound to translate into patients receiving better treatment. Increasing the capabilities of GHs, however, also impacts transfer selection.Cases that required transfers in the past may not anymore; patients who were on the line between transfer or not because of the associated risks will probably now stay for treatment in the GH. Thus, this component should squeeze transfers in the middle. In 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

In this section I introduce a model that enables a deeper understanding of the effects presented in the previous section. It analyzes physicians' decisions at GHs about how to treat heart attack patients. 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 if the expected return in terms of survival probability is high enough to make the investment worthwhile. The model is consistent with the mechanisms discussed above. The least severe patients will not require transfers, and the most severe will not be able to get them. Moreover, reducing the transfer cost (by improving coordination) would increase the number of transfers and improve the survival of more complicated patients, while improving capabilities would lead to fewer 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 two kinds of hospitals, GH and RC, with $\lambda_{GH} < \lambda_{RC}$.

3. Each hospital/patient combination matches into a survival probability function $S(\delta_i, \lambda_j)$, where their survival probability increases with the hospital's capabilities and decreases with the 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. The transfer of patients is possible, but not free. We assume there is a fixed cost *c* in terms of severity. Patient i with an initial level of severity δ_i becomes $\delta_i(1 + c)$ after her transfer due to the increased time before treatment, which worsens health conditions. Note that this effect is greater the more severe a patient is, which is consistent with (Scholz et al., 2018).

5. Lastly, hospitals use a threshold κ to determine whether a transfer is justified. A patient is transferred from a GH to an RC if $S(\delta_i(1 + c), \lambda_{RC}) - S(\delta_i, \lambda_{GH}) > \kappa$. The κ parameter captures the fact that a patient would probably not be transferred if the return to doing so was very low.

6. 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 cumulative distribution function 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 displays some of these potential shapes. Critically, given α, the higher the value of capabilities, the better the patient does and the higher the δ, the worse the patient's outcome. Figure 10 presents how the survival function appears for several potential values of λ_j once α is fixed. When λ_j is very small, the likelihood of survival is very low and rises as λ_j increases; a higher λ_j always dominates a smaller one. Moreover, the whole space is covered by different 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 explain the mechanisms operating in the model in more depth by exploring decisions about whether to transfer a patient. A patient could benefit from being transferred from a GH to an RC if their probability of survival is higher, even after accounting for the cost of a transfer in terms of severity. Since the transfer cost increases with severity, the most complicated patients will not be transferred. Moreover, the least complicated patients would have a slight benefit of transfer, but their chances of survival are pretty high anywhere. The benefit of a transfer is greater for patients in the middle, since they could truly benefit from more advanced technology and can withstand the ride to a different hospital.

Doctors must assess whether each patient's transfer is worth it. In the model, a patient will be transferred to an RC if his survival probability after a transfer is at least κ higher than if he stays. Figure 11 displays these patterns in four lines. The blue line with long dashes captures the survival function for GH. The red line represents the survival function for RC. It dominates the blue line since $\frac{\partial}{\partial \lambda_j} s(\delta_i, \lambda_j) > 0$. The purple dotted line reflects a patient's survival probability after a transfer: $S(\delta_i + c \cdot \delta_i, \lambda_{RC})$. This line is lower than the RC because of the cost that has to be paid for the transfer. 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; it represents the survival probability after transfer but is 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 demonstrates that it is reasonable for doctors to transfer individuals who would receive a substantial benefit from being moved to a different hospital. If every patient with a small benefit were transferred, then physicians would request an ambulance to transfer many people with headaches on the off chance it could be something else. The model shows that transfers always happen in the middle if $\kappa > 0$. 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 focuses on enhancing coordination by using more efficient communication. Creating 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. It displays the same four 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 (especially severe patients) are now more likely to survive after a transfer. This happens because the cost is increasing in terms of severity, and thus a reduction yields greater benefits for them. Thus there would be additional transfers, and 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 the program's implementation and would be transferred now. The image shows a substantial change in the patient's probability of survival. The mechanism driving this effect is that if the cost of transfer is relatively high, as it is for this patient, a transfer becomes too expensive in terms of health and the patient cannot access 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 program's second component involves improving the capabilities of the GHs (reflected in the model by a higher λ_{GH}). Figure 14 highlights the same four lines from 11 in red, and the shift in capabilities for GH in blue. The shift induces a slight improvement for patients across severities and reduces transfers towards the middle. This pattern reflects that the patients who were just below and just above the threshold of being considered worth transferring no longer represent a worthwhile transfer case.

These mechanisms help illuminate why the productivity gap is such an important driver of the program's success. If there is a very small productivity gap between GHs and RCs, there will be little to gain from transfers, even when costs are 0. Moreover, if costs are high but there is a significant gap, the communication channel could still induce a positive change. That is, even if the GH 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 first need to be able to identify the structural parameters based on the data. Note that the model has five parameters $(\lambda_{GH}, \lambda_{RC}, c, \kappa, \alpha)$. Since the intervention potentially affects the capabilities at both GH and RC hospitals as well as the cost of transfers in terms of health, we end up with a total of eight parameters to estimate: $(\lambda_{GH0}, \lambda_{GH1}\lambda_{RC0}, \lambda_{RC1}, c_0, c_1, \kappa, \alpha)$. Therefore we need eight data moments along with an estimation of the severity distribution to estimate our results. We utilize the following moments in the data to estimate the model's structural parameters:

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 give us eight structural parameters and eight moments in the data. To avoid introducing bias and capturing shifts that are not caused by the intervention, I define the moments before the intervention based on the pre-CI mean for the treatment group and the post-intervention moments as the same moments but shifted by the reduced-form estimates from Section 5. Table 11 shows the moments we utilize. I estimate the model through the general method of moments (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 indicates transfer and $\hat{\beta}_i$ the reduced-form estimate of the CI effect on the data moment.

Finally, I must calculate the severity distribution. I do so by adapting different machine-learning prediction models of mortality. I utilize 2014 as the baseline training year for every heart attack since the CI was launched until February 2015. Exploiting the fact that I have data for every IMSS hospitalization from 2013 to 2019, I create a model that incorporates every hospitalization of each heart attack patient in the 12 months prior to the event, including how many nights he spent in the hospital over the last year, which ICD-10 code matches his diagnosis, and demographic variables such as age, sex and hour of entry, day of the week of entry, and month of entry. Importantly, 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 subsequent years. Table 12 shows the mean squared errors I obtain from this exercise; it demonstrates that all methods behave almost equally well. Figure 15 displays the histogram for the Lasso prediction, which is what I use to indicate severity from now on. [10]

Based on the above equations I estimate the structural parameters. Table 13 reports our estimations. As expected, there is a slight improvement in GHs' capabilities from 1.8 to 2.2 and a considerable improvement in transfer costs: the parameter decreases from 1.6 to 1, which corresponds to nearly a 40% reduction in the cost of transferring a patient. Moreover, the threshold for transferring a patient is estimated to be 0.15, which indicates that a doctor considers a transfer to be worthwhile if it is expected to improve the patient's chance of survival by at least 15%.

To better understand what is happening, 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 the CI program's implementation. The pre-period adjusted model is shaded. Overall, the graph shows that there was virtually no change in RC capabilities, there was a slight improvement in GH skills, and transfer costs decreased significantly. Moreover, the figure shows that as a consequence of these changes, more complicated patients are now being transferred than before, and some less severe patients now do not require a transfer.

To assess the model's explanatory power, we can compare its predictions to the transfer patterns we observe with the estimated severity, which we can observe without imposing any restrictions. Figure 17 illustrates the transfer pattern before and after. This 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 hand, there are additional transfers of more complicated patients; on the other hand, there are fewer transfers of less severe patients. These comparisons suggest that the model is well equipped to explain the intervention's mechanisms. In the next section we use the model to assess each component's contribution.

6.1.4 Counterfactual Policy Simulation

We next employ the estimated structural parameters to undertake a counterfactual policy estimation. We ask how much of the contribution would have happened if the capabilities component of the program

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

were not included. I calculate the survival probability before the intervention using the parameters we obtain from the model, and then repeat the exercise but changing c_0 for c_1. Figure 18 illustrates how the model shifts. The probability of survival increases by 8pp, which is 68% of the effect. Moreover, we calculate that transfers would have been at 40% without the capabilities component—substantially more than what we observe in the data.

I also perform the same exercise to determine the contribution that the capabilities component would have had on its own (see Figure 19). I find a comparable increase of 7.5pp (64% of the total) without the communication channel. This highlights that the capabilities improvement was effective as well. In this scenario, we find that no transfers would take place because the increase in capabilities makes every transfer prohibitively expensive. This would be a consequence of keeping costs high but reducing the skill gap between the sender and receiver.

The fact that the sum of each component's contribution equals 132% of the total effect highlights that the communication and capabilities channels substitute for each other. Since the main benefit of the communication channel stems 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 GH that they will not use. Similarly, patients who will not require a transfer given the simultaneous increase in capabilities will not enjoy the benefit of improved coordination.

The lessons drawn from this analysis highlight four important takeaways for policy makers. First, the communication channel is extremely easy to implement, and whenever there is a large enough productivity gap, it would probably be effective. Second, when reducing communication barriers, one should be aware of the induced increase in transfers and make sure there is enough supply to handle the increased demand. Third, increased capabilities can also be effective and lead to a reduction in transfers. Fourth, given that both components are substitutes, policy makers should consider which is the best fit for their context before deciding which one to implement. Generally, when there is considerable fragmentation and a substantial skill gap, the communication channel probably generates higher returns. However, when there is a small skill gap or the additional demand for transfers cannot be met, an investment in capabilities might be worthwhile.

7 Concluding Remarks

Over the past few decades, several nations have stressed the use of ICT in healthcare as a mechanism to improve efficiency and clinical outcomes. However, after spending several billions of dollars to create a centralized EHR with health information exchange capabilities, the literature suggests there have been only small effects with vast heterogeneity. One of the main explanations for this finding is that the systems do not communicate well with each other. This project addresses a simple yet powerful idea of how to improve coordination: leveraging widespread technologies.

The paper evaluates the CI program implemented by Mexico's largest healthcare provider. CI aims to reduce the time to treatment for heart attack patients in IMSS hospitals by enhancing (1) communication (through chat groups) and (2) 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 GHs that exhibit a significant survival rate gap relative to the more advanced RCs to which they send transfers. Such hospitals improve their survival rate by 29% (11.7 pp), increase transfers by 85% (5pp), and reduce the transfer time by 30% (4 hours).

The paper employs a structural model to interpret the reduced-form results and explain that the pattern of increased effectiveness arises in hospitals with a larger skill gap because they have more to gain from transfers. By estimating the structural parameters, the model presents a counterfactual policy analysis and isolates each component's contribution to the program. The results suggest that the communication channel alone would have generated 68% of the total effect (8pp), highlighting the potential of leveraging widespread technologies. 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, mainly because patients who are transferred cannot enjoy better service at the GH, and patients who stay do not receive the benefits of transfers.

Fragmentation is one of the most important challenges facing health networks today, as the lack of coordination and efficient communication across physicians hinders their ability to provide high-quality and timely care. In this paper, I provide evidence of ICT's significant potential to reduce fragmentation and improve health outcomes. Moreover, through the lens of a structural model, I find that ICT interventions have a higher potential when there is a large productivity 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-related ICT.

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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 (0.002)	0.748 (0.003)	0.612 (0.002)	0.592 (0.003)	0.880 (0.006)
Transfer Rate			0.0689 (0.001)		
GH Arrival	0.617 (0.002)				
Male	0.650 (0.002)	0.676 (0.003)	0.633 (0.002)	0.623 (0.002)	0.778 (0.008)
Age	65.46 (0.062)	64.31 (0.114)	66.17 (0.071)	66.46 (0.074)	62.31 (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*** (0.014)**	**0.025** (0.011)**	**-4.135*** (1.559)**	**0.020 (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: Productivity-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*Productivity gap	**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: Productivity-Gap Group Analysis

	Survival Rate (GH Arrivals)	Transfer Rate (GH Arrivals)	Transfer time (GH Arrivals)
	(1)	(2)	(2)
Tpost*(Low gap)	**-0.019**	**0.022**	**-3.422***
	(0.032)	**(0.019)**	**(1.803)**
Tpost*(Medium gap)	**0.015**	**0.005**	**-4.545****
	(0.018)	**(0.012)**	**(2.083)**
Tpost*(Large gap)	**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*(Low gap)	**-0.026**	**0.020**
	(0.033)	**(0.047)**
Tpost*(Medium gap)	**0.019**	**0.038**
	(0.025)	**(0.041)**
Tpost*(Large gap)	**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.

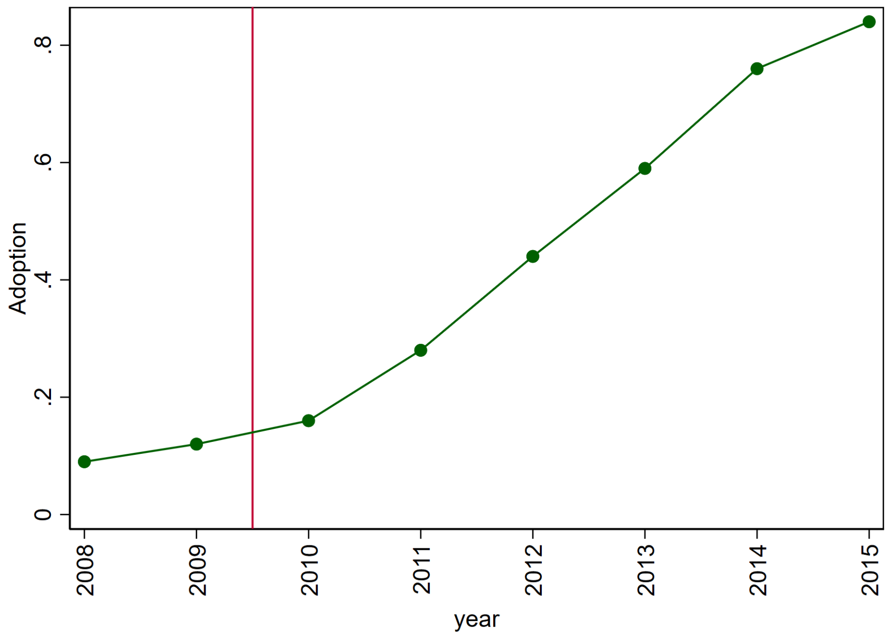
Table 13: Structural Parameters

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.

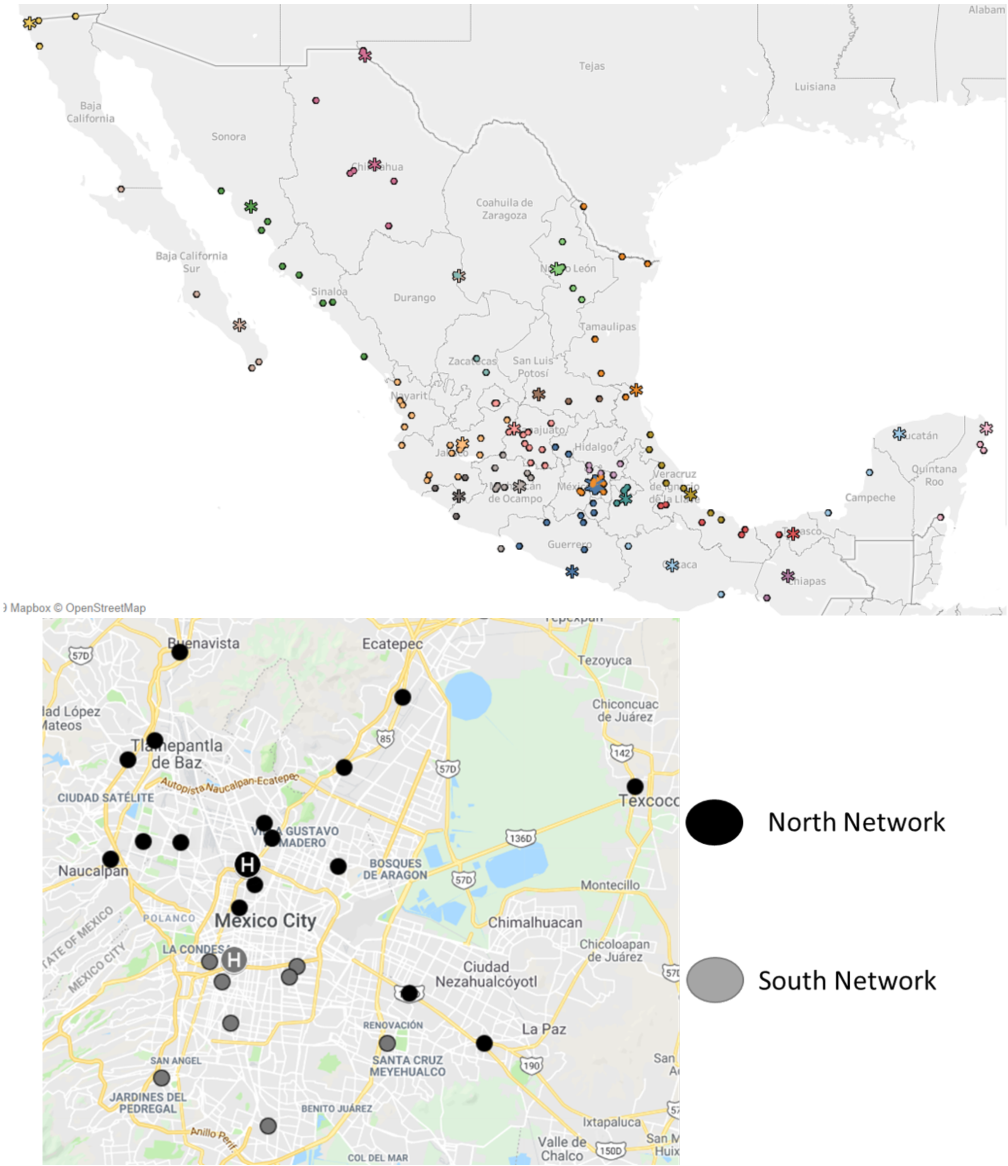
Figures

Figure 1: Electronic Health Records (EHR) Adoption



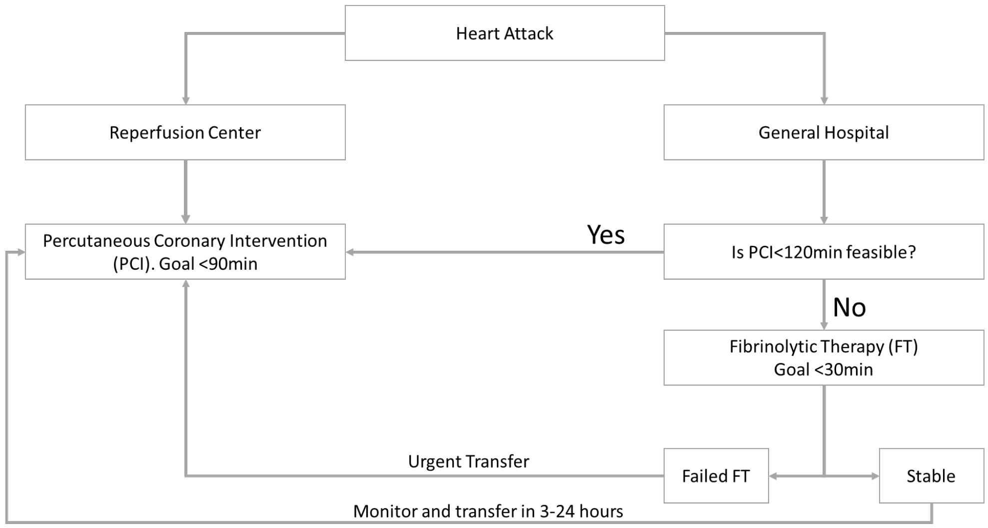
Notes: This figure presents estimates of the fraction of hospitals who were using "Basic EHR without clinician notes" in the year indicated. The points official estimates from the Office of the National Coordinator (ONC) of Health Information Technology (re-weighted to correct for nonrandom sample response).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

Figure 2: IMSS' heaart attack networks



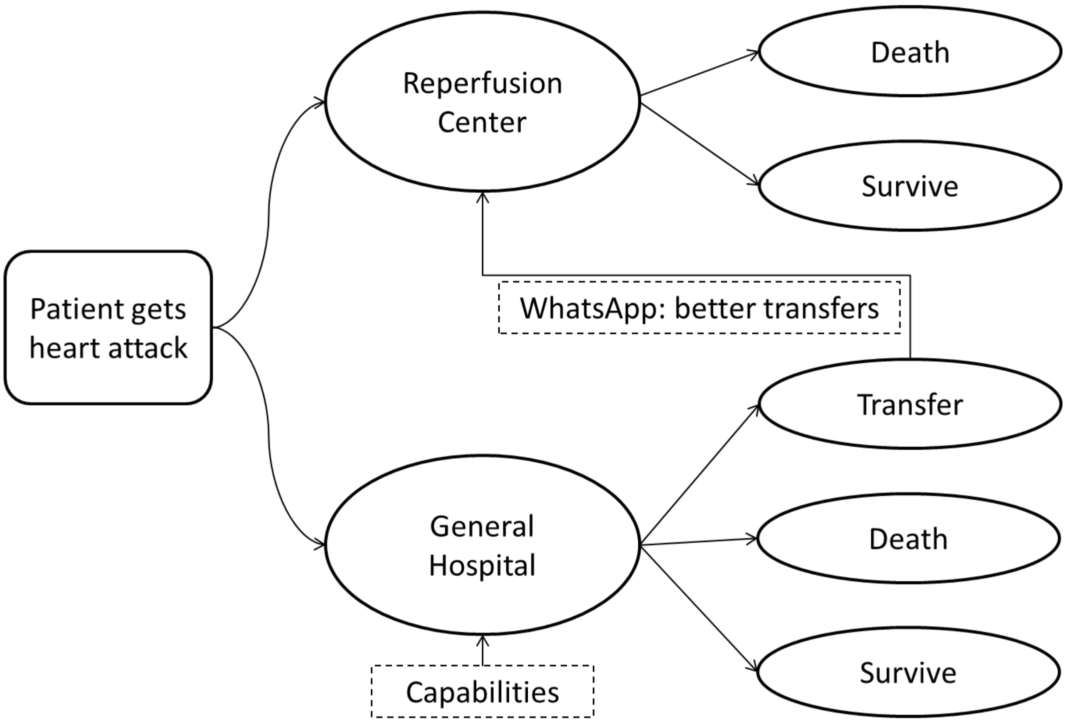
Notes: This figure presents the overall map of IMSS heart attack networks and a close up on the 2 networks that are in Mexico CIty.

Figure 3: Survival Function



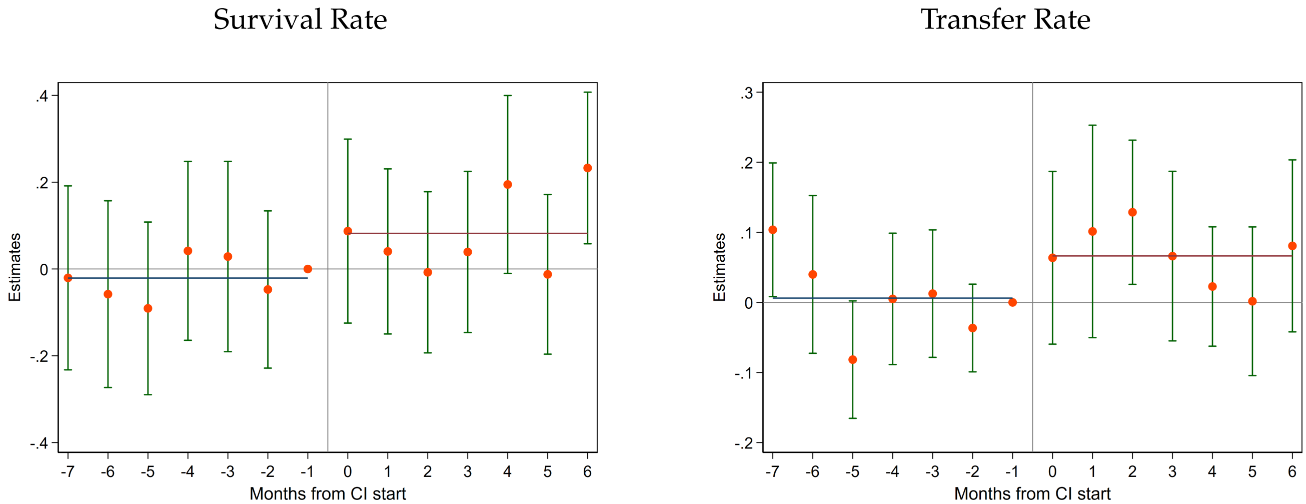
Notes: This figure summarizes the algorithm recommended by the ACCF/AHA guideline for the management of ST-elevation myocardial infarction: a report of the American College of Cardiology Foundation/American Heart Association Task Force on Practice Guidelines.

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.

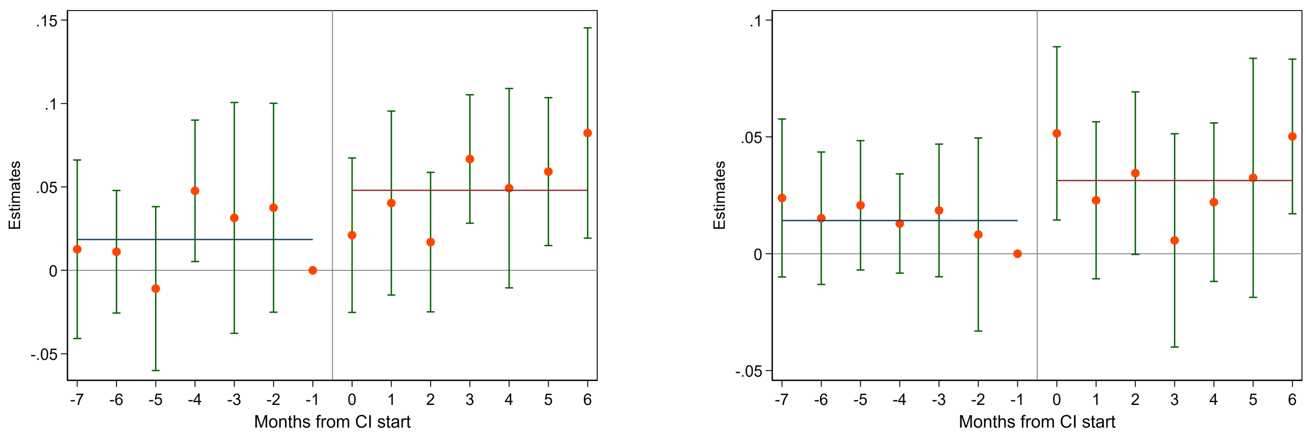
Figure 5: Event Studies for Mexico City



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.

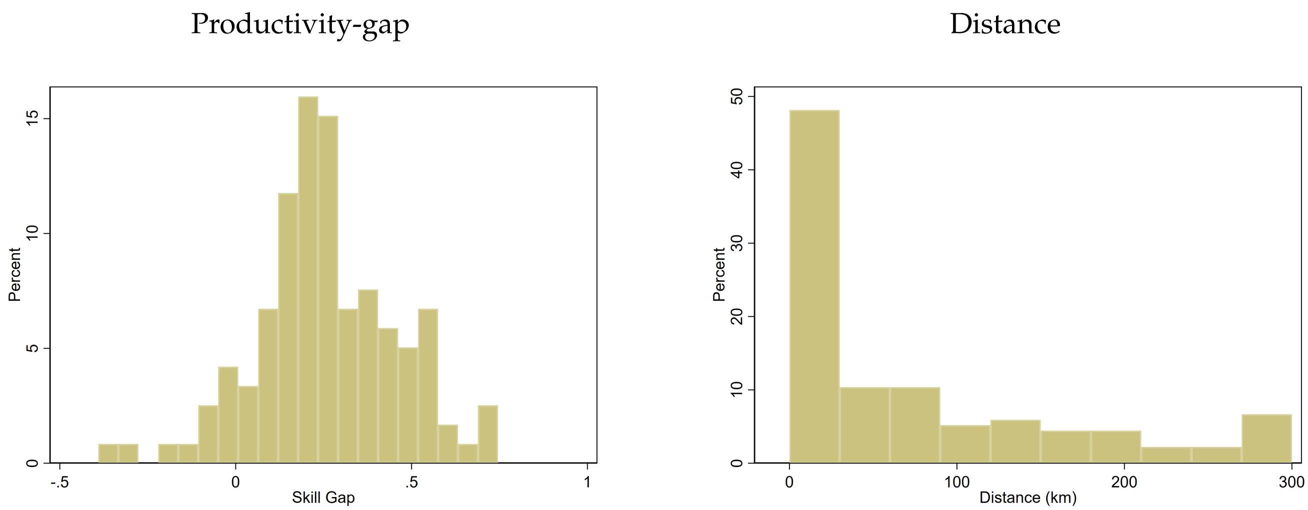
Figure 6: Event Studies for Stacked Data

Survival Rate | Transfer Rate



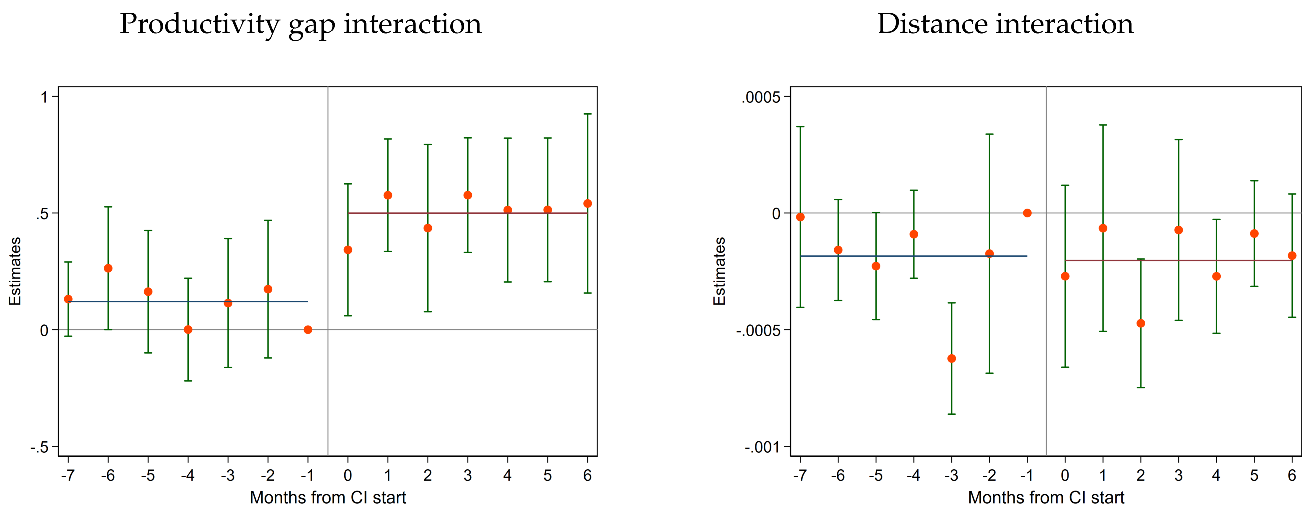
Notes: This figure presents the results from the CI program on survival rate when arriving first to a general hospital urgent wing and the effect on transfers. I control for expansion/hospital fixed effects, month fixed effects and relative time to starting the program. Moreover I cluster standard errors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

Figure 7: Productivity-Gap and Distance Histograms



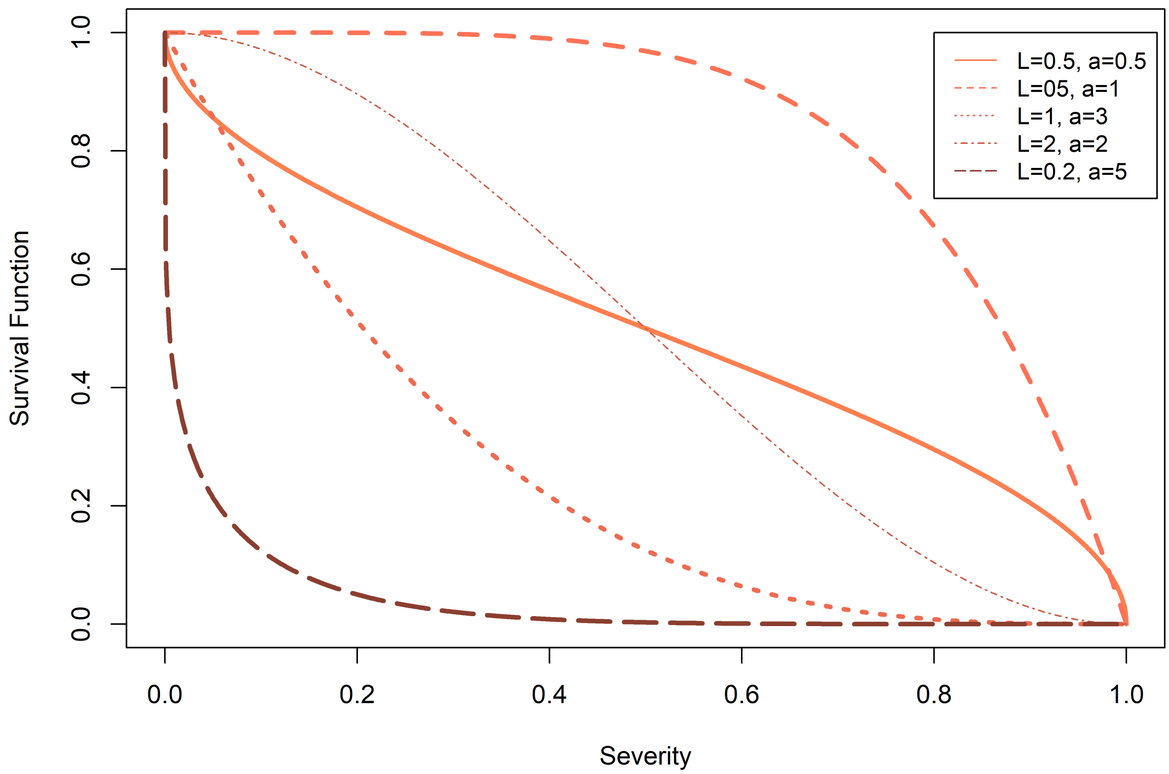
Notes: This figure presents the histograms from the distance in km between general hospitals and reperfusion centers and the skill gap defined as survival rate upon arrival between general hospitals and reperfusion centers

Figure 8: Event Studies for Interaction



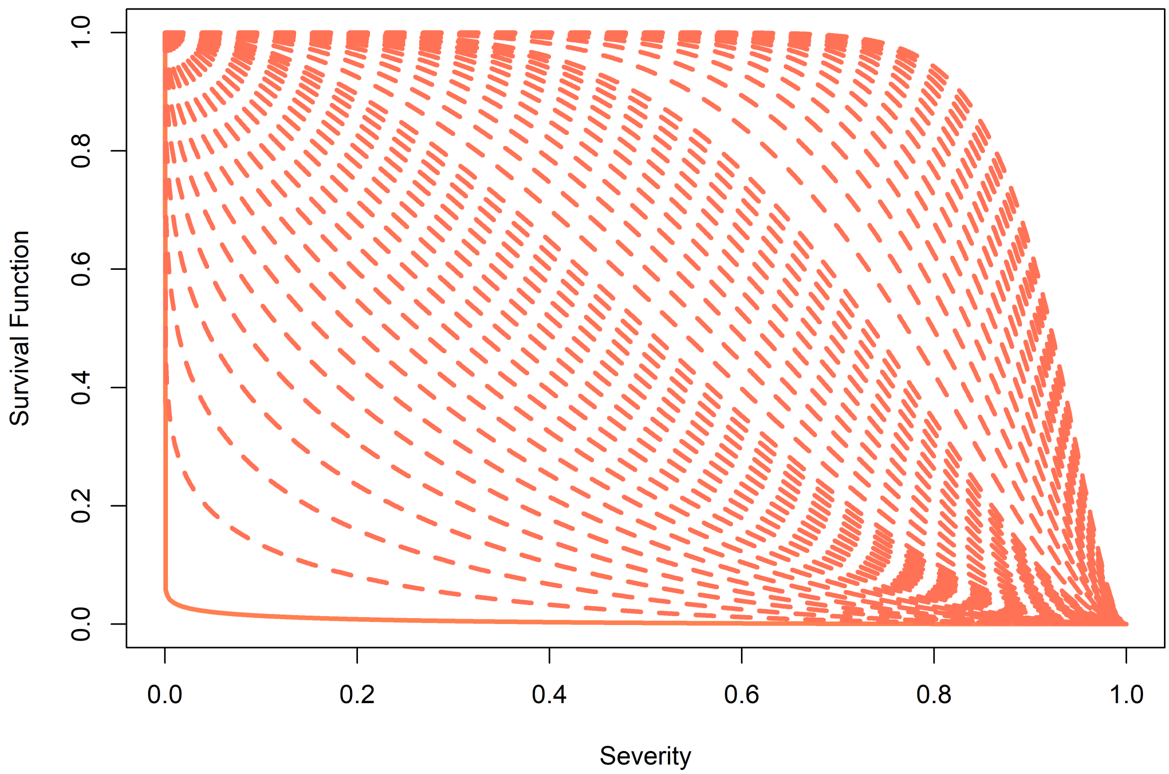
Notes: This table presents the interaction coefficients when interacting Tpost with the skill-gap or distance following 1. I control for expansion/hospital fixed effects, month fixed effects and cluster standard errors at the network/expansion level. 95% confidence intervals are reported.

Figure 9: Survival Function



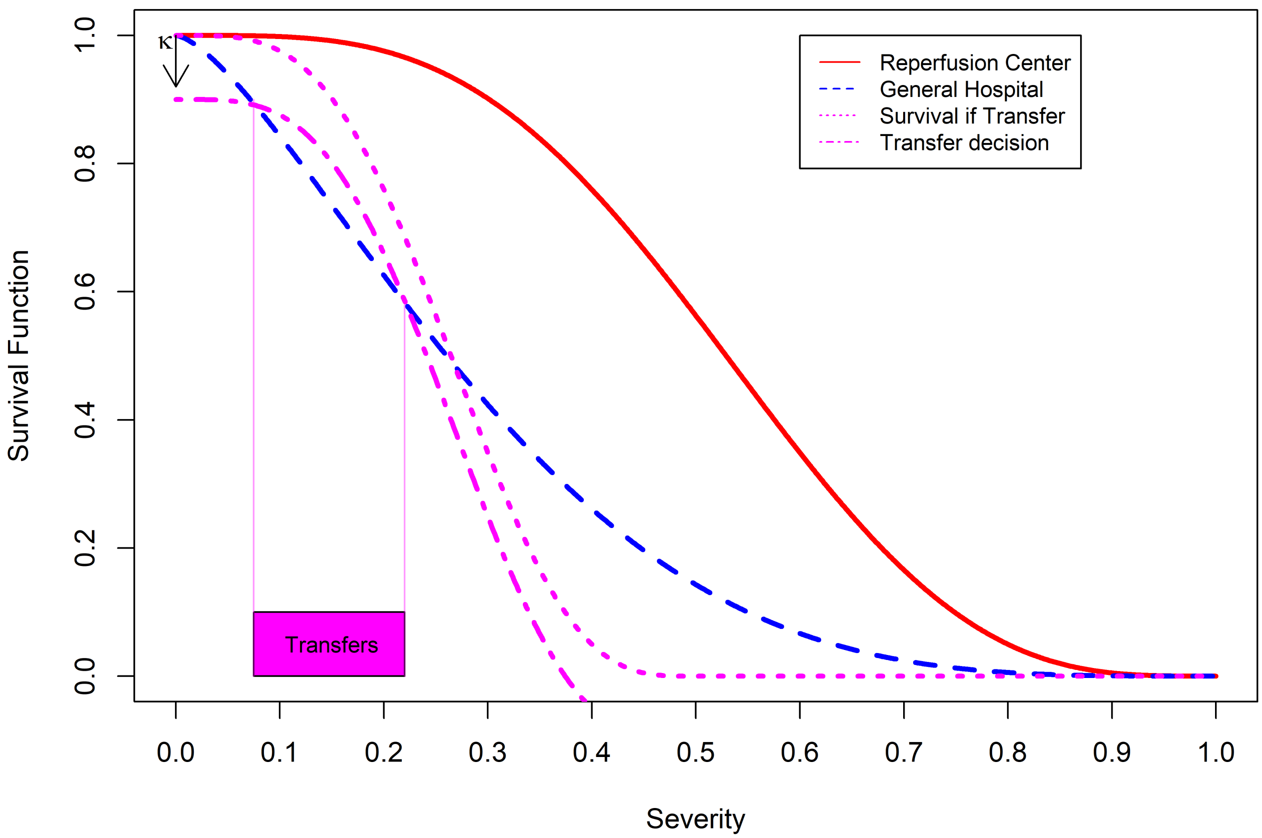
Notes: This figure represents the different functional shapes that the defined survival function can take.

Figure 10: Survival Function



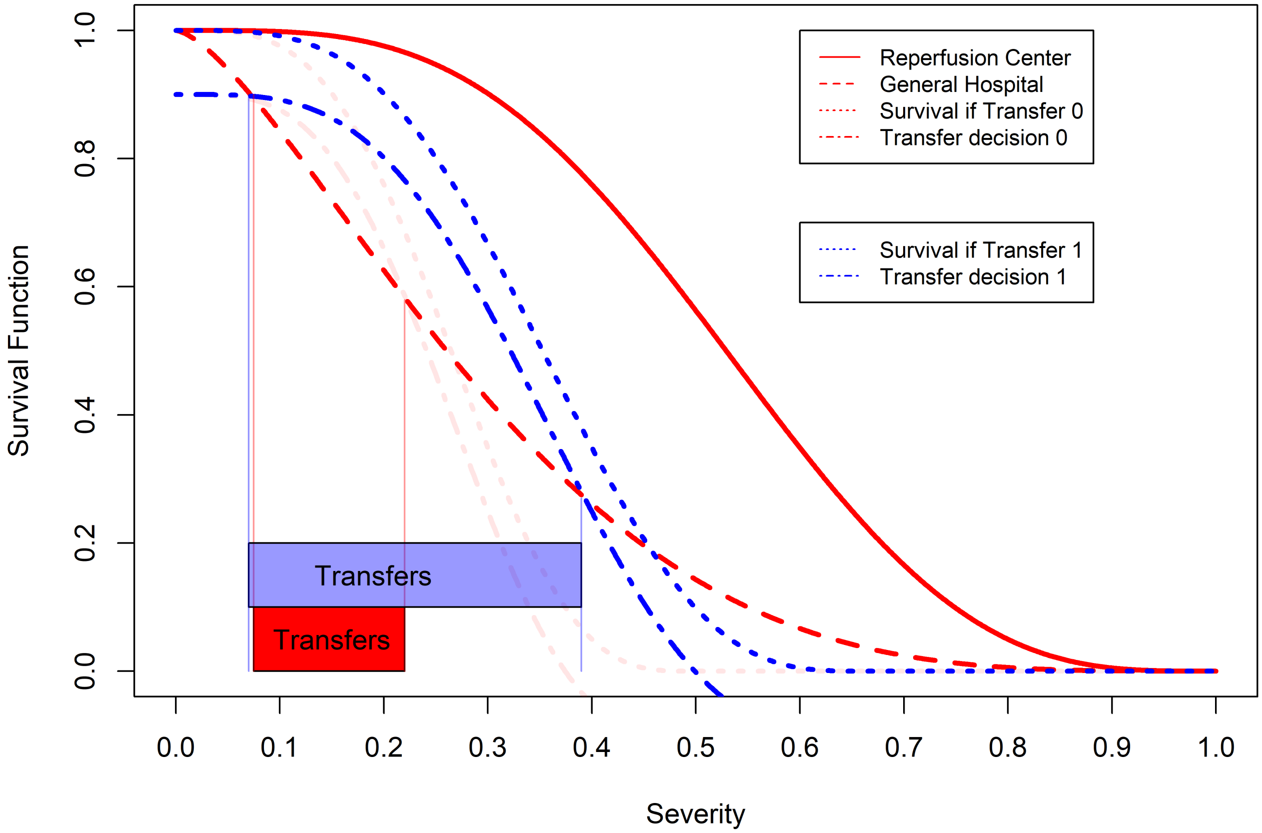
Notes: This figure presents how once α is fixed, a higher λ provides a better opportunity to live for every heart attack patient.

Figure 11: Transfer Decision



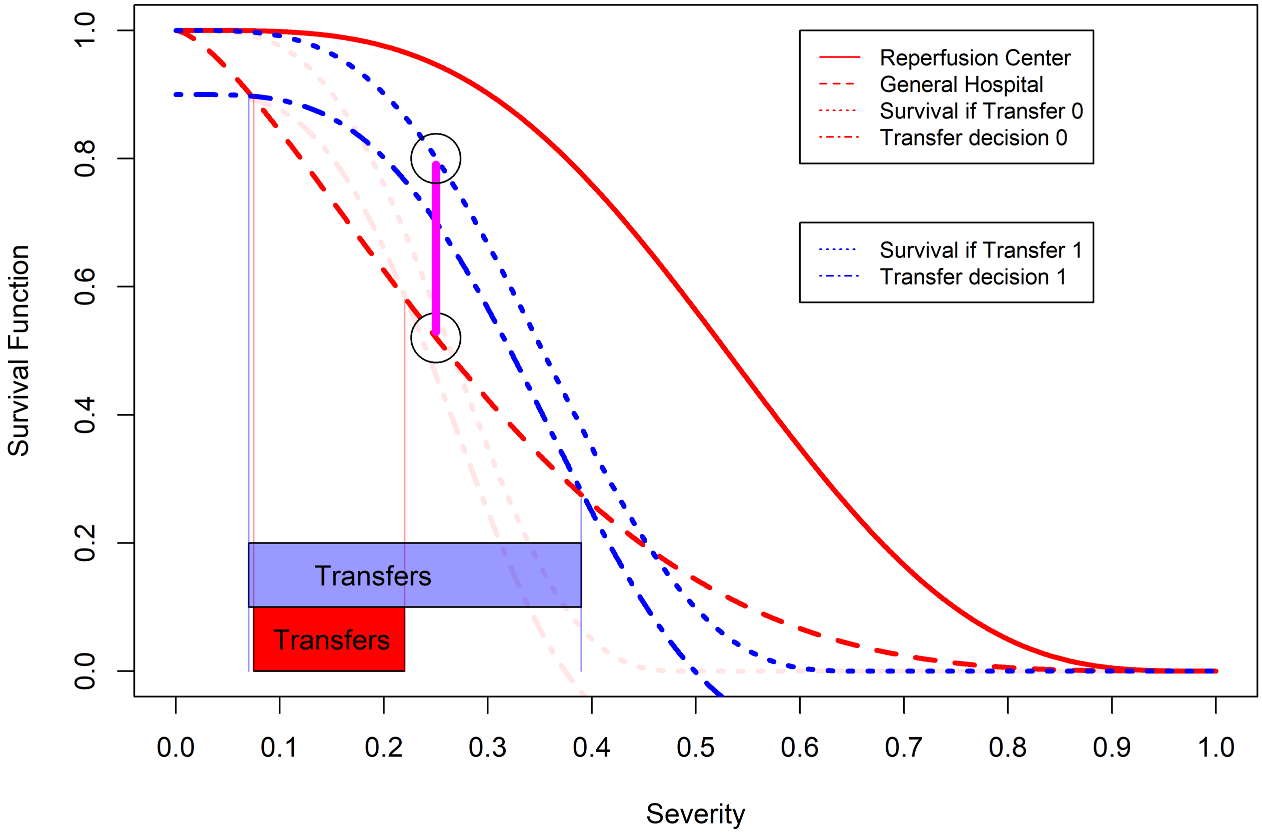
Notes: There are 4 lines in the image. The Blue line with long dashes captures the survival function for GH. The red line represents the survival function that RC face. It dominates the blue line since $\frac{\partial}{\partial \lambda_j} s(\delta_i, \lambda_j) > 0$. The purple dotted line reflects the 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



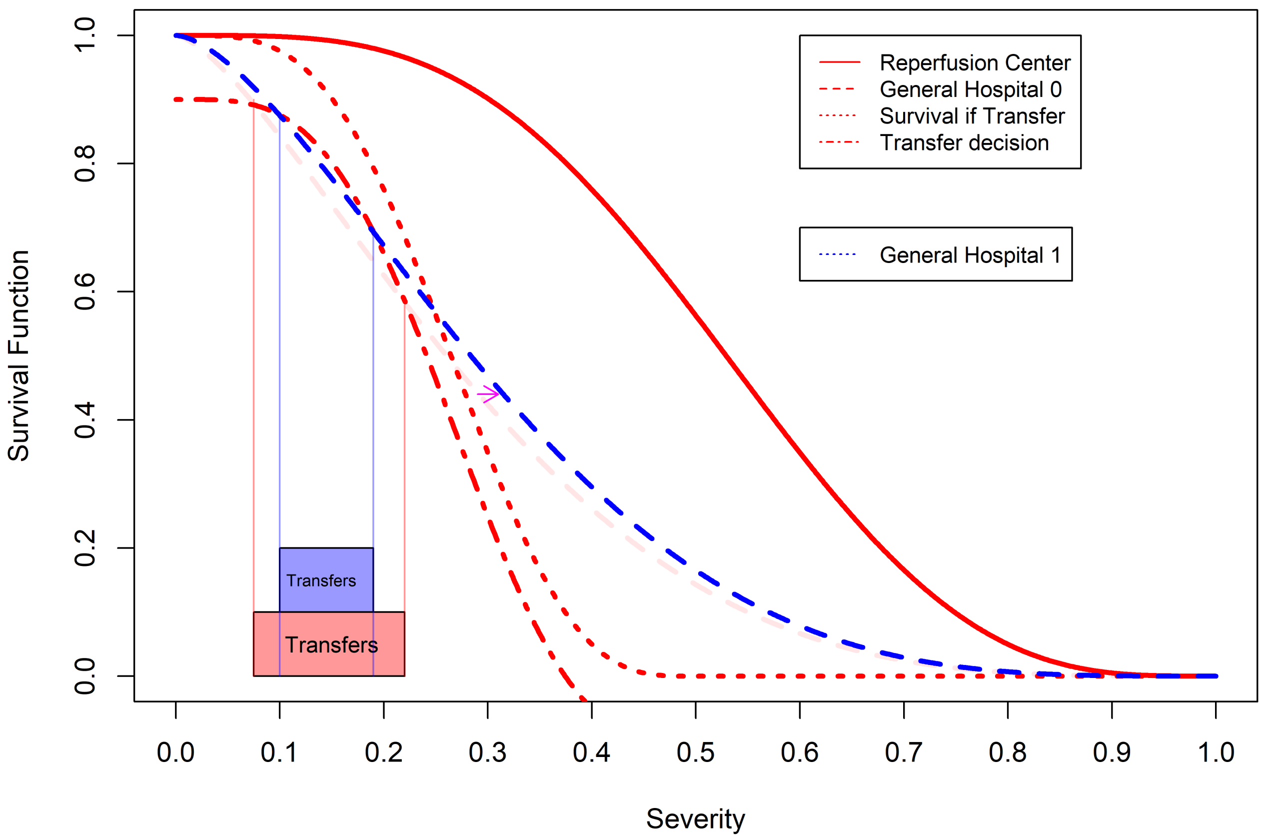
Notes: On the figure we can see the same 4 lines from 11 in red along with how the survival if transfer and transfer decision lines would look under a lower c. We can see that patients would now face a bigger survival probability after transfer, especially among more severe patients. This happens because 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



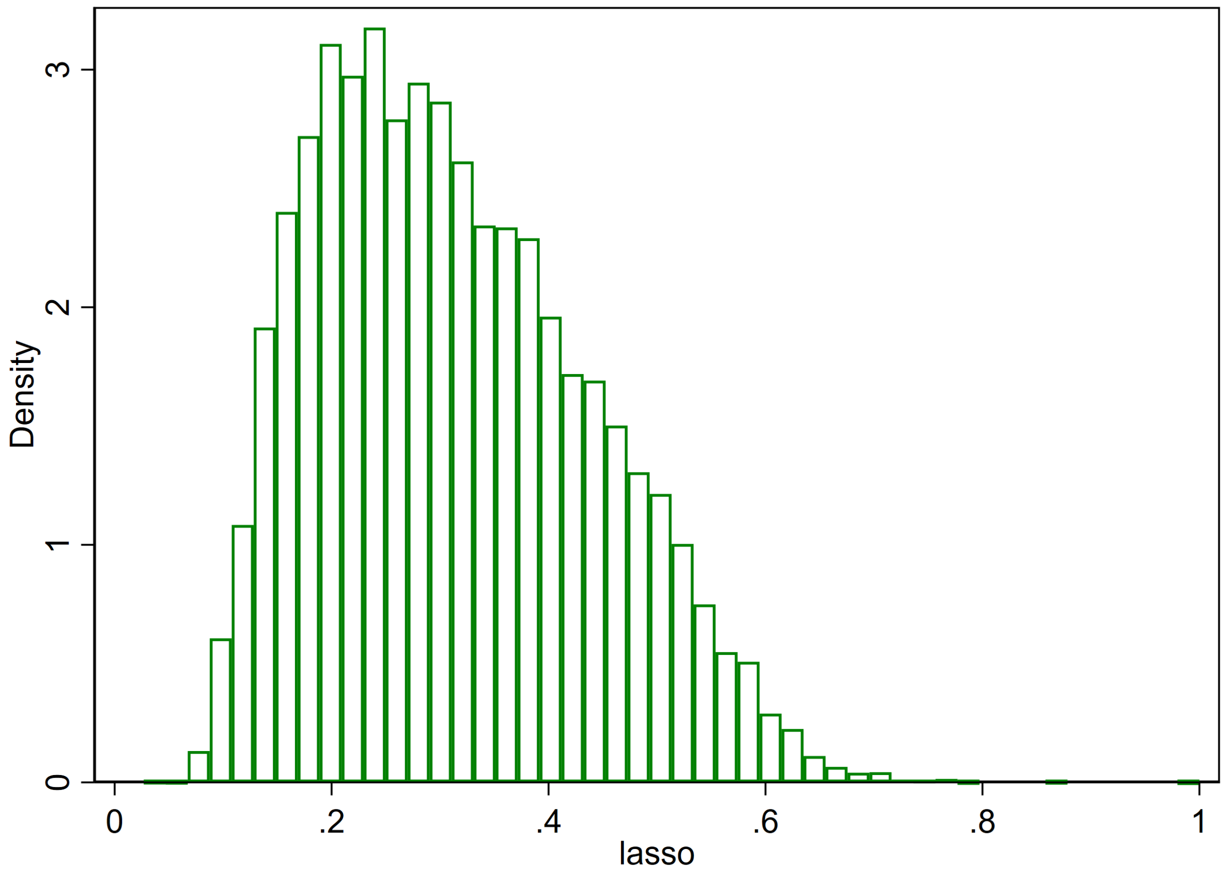
Notes: On the figure we can see the same 4 lines from 11 in red along with how the survival if transfer and transfer decision lines would look under a lower c. We can see that patients would now face a bigger survival probability after transfer, especially among more severe patients. This happens because 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}



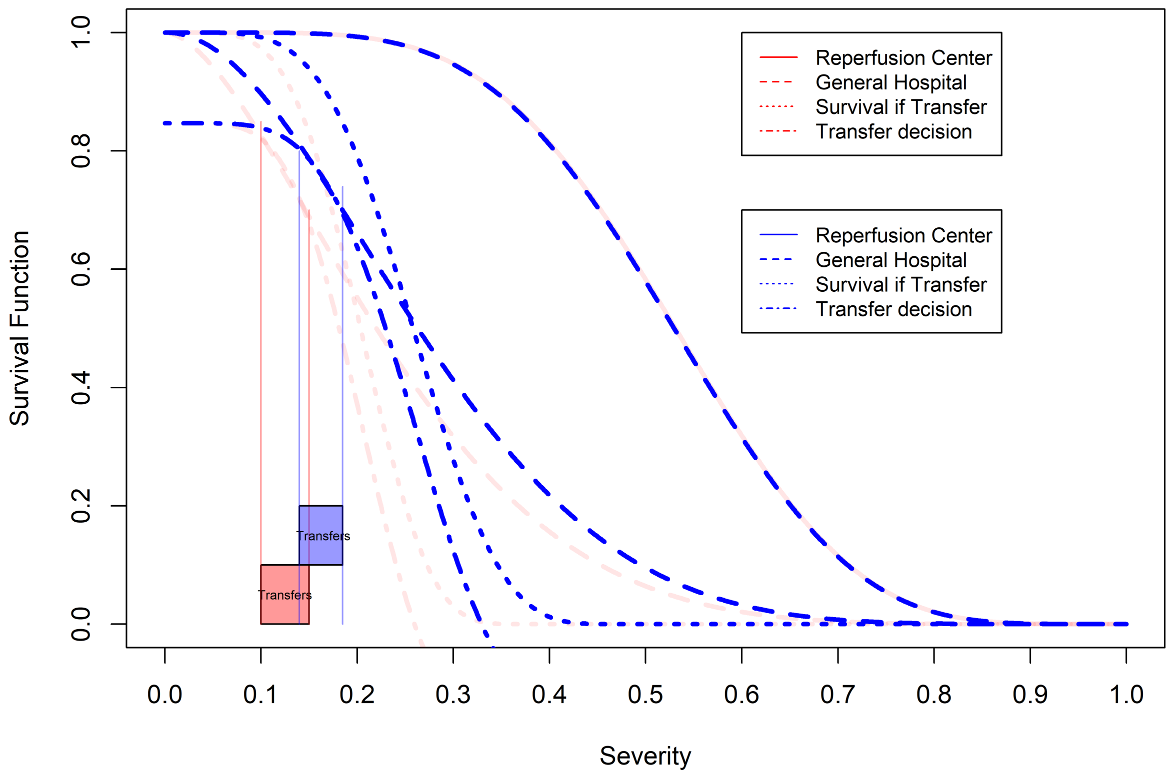
Notes: The figure highlights the same 4 lines from 11 in red along with how the shift in capabilities for general hospitals in blue. We can see that the shift induces a slight improvement for patients across severities and reduces transfers towards the middle. This pattern reflects that least and more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

Figure 15: Severity Estimation



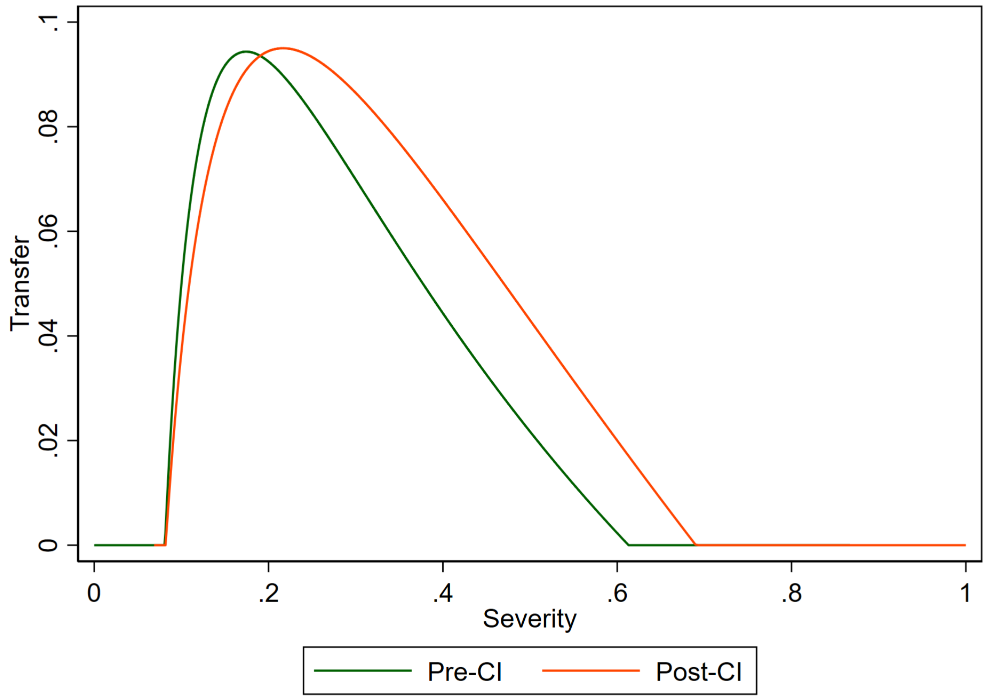
Notes: This figure presents the histogram of the estimated severity distribution that we have. This estimation was based on utilizing the year 2014 as the training data since no network had undergone the CI program and predicting for probability of death values for the rest. The data incorporates demographic 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



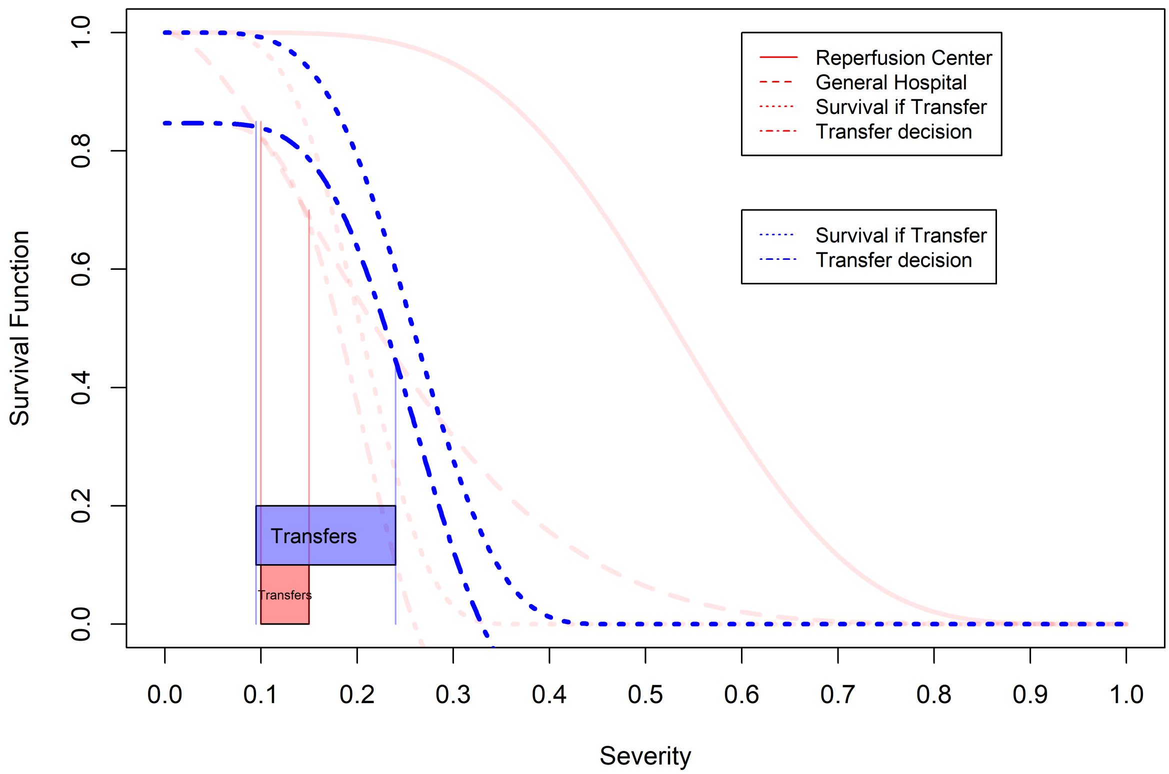
Notes: This figure presents how the estimated model looks before and after the CI program. The before estimations are shaded in the image. We can see that there is a big reduction in communication costs and a slight improvement in GH capabilities.

Figure 17: Transfers vs Estimated Severity



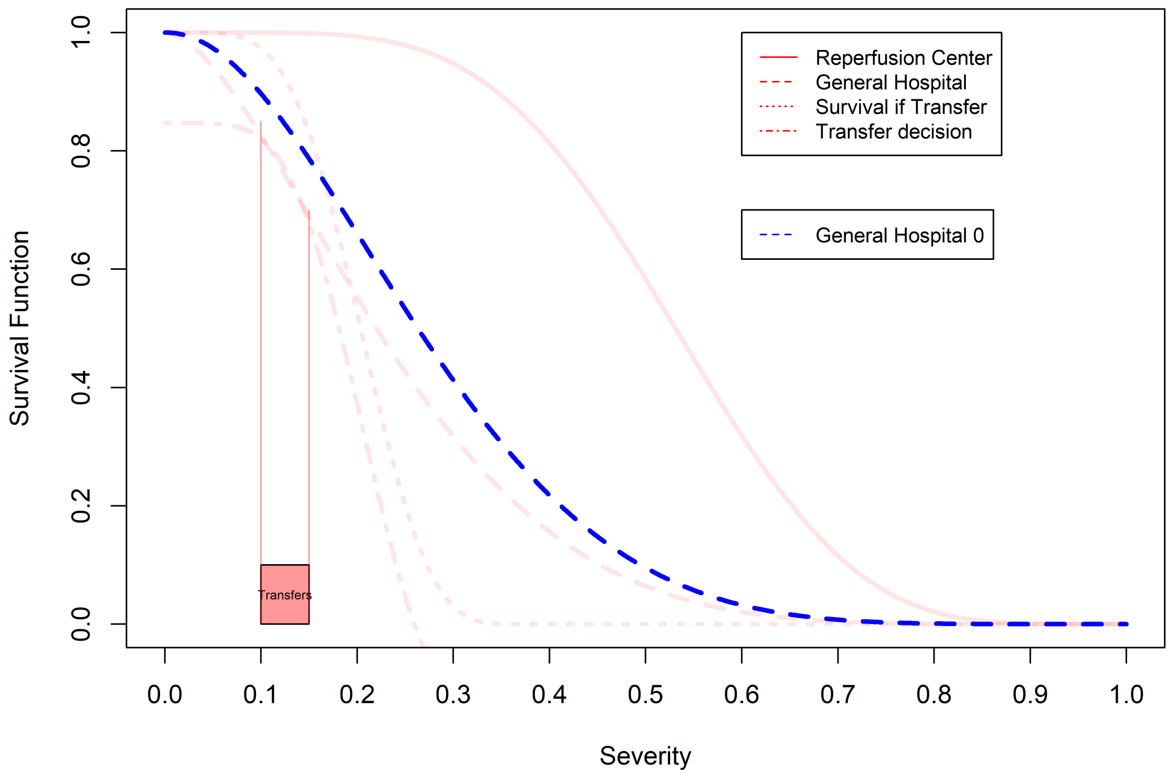
Notes: This figure represents the mean transfer rate observed in the data by estimated severity. Estimates were created using fractional polynomials

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.

References

AGHA, L. (2014): "The effects of health information technology on the costs and quality of medical care," *Journal of Health Economics*, 34, 19–30. [6]

AGHA, L., B. FRANDSEN, AND R. J. B. (2019): "Fragmented division of labor and healthcare costs: Evidence from moves across regions." *Journal of Public Economics*, 169, 144–159. [6]

ATASOY, H., B. N. GREENWOOD, AND J. S. MCCULLOUGH (2019): "The Digitization of Patient Care: A Review of the Effects of Electronic Health Records on Health Care Quality and Utilization," *Annual Review of Public Health Annu. Rev. Public Health*, 13, 487–500. [6]

ATHEY, S. . AND S. STERN (2002): "The impact of information technology on emergency health care outcomes," *The Rand Journal of Economics*, 33. [6]

BLOOM, N., C. PROPPER, S. SEILER, AND J. V. REENEN (2013): "The impact of competition on management quality: Evidence from public hospitals," *Review of Economic Studies*, 82, 457–489. [7]

BLOOM, N. AND J. VAN-REENEN (2011): *Human resource management and productivity*, vol. 4. [7]

BORRAYO-SÁNCHEZ, G., G. PÉREZ-RODRÍGUEZ, O. G. MARTÍNEZ-MONTAÑEZ, E. ALMEIDA-GUTIÉRREZ, E. RAMÍREZ-ARIAS, J. ESTRADA-GALLEGOS, N. M. PALACIOS-JIMÉNEZ, M. R. PERALTA, E. A. URIBE, AND J. A. DÁVILA (2017): "Artículos de opinión," *Rev Med Inst Mex Seguro Soc*, 55, 233–279. [7]

BRONSOLER, A., J. DOYLE, AND J. V. REENEN (2021): "The Impact of Healthcare IT on Clinical Quality, Productivity and Workers," *National Bureau of Economic Research.* [7]

CANNON, C. P., C. M. GIBSON, C. T. LAMBREW, D. A. SHOULTZ, D. LEVY, W. J. FRENCH, J. M. GORE, W. D. WEAVER, W. J. ROGERS, AND A. J. TIEFENBRUNN (2000): "Relationship of Symptom-Onset-to-Balloon Time and Door-to-Balloon Time With Mortality in Patients Undergoing Angioplasty for Acute Myocardial Infarction," . [7]

CHAN, D. C. (2015): "Teamwork and Moral Hazard: Evidence from the Emergency Department *," . [7]

CHANDRA, A. AND D. O. STAIGER (2007): "Productivity Spillovers in Health Care: Evidence from the Treatment of Heart Attacks," *Journal of Political Economy*, 115. [7]

CORDERO, A., R. LÓPEZ-PALOP, P. CARRILLO, A. FRUTOS, S. MIRALLES, C. GUNTURIZ, M. GARCÍA-CARRILERO, AND V. BERTOMEU-MARTÍNEZ (2016): "Changes in Acute Coronary Syndrome Treatment and Prognosis After Implementation of the Infarction Code in a Hospital With a Cardiac Catheterization Unit," *Revista Española de Cardiología (English Edition)*, 69, 754–759. [7]

DAUERMAN, H. L., E. R. BATES, M. C. KONTOS, S. LI, J. L. GARVEY, T. D. HENRY, S. V. MANOUKIAN, , AND M. T. ROE (2015): "Nationwide Analysis of Patients With ST-Segment–Elevation Myocardial Infarction Transferred for Primary Percutaneous Intervention: Findings From the American Heart Association Mission: Lifeline Program," *Circulation: Cardiovascular Interventions 8, no. 5 (2015): e002450.* [7]

DESHPANDE, M. AND Y. LI (2019): "Who is screened out? application costs and the targeting of disability programs," *American Economic Journal: Economic Policy*, 11, 213–48. [12]

DRANOVE, D., D. KESSLER, M. MCCLELLAN, AND M. SATTERTHWAITE (2003): "Is More Information Better? The Effects of "Report Cards" on Health Care Providers," *Journal of Political Economy*, 111. [7]

GNANLET, A., M. CHOI, AND S. DAVOUDPOUR (2019): "Impediments to the Implementation of Healthcare Information Technology: A Systematic Literature Review," *Journal of Supply Chain and Operations Management*, 17. [7]

GÓMEZ-HOSPITAL, J. A., P. D. DALLAGLIO, J. C. SÁNCHEZ-SALADO, A. ARIZA, S. HOMS, V. LORENTE, J. L. FERREIRO, J. GOMEZ-LARA, R. ROMAGUERA, J. SALAZAR-MENDIGUCHÍA, L. TERUEL, AND ÁNGEL CEQUIER (2012): "Impact on Delay Times and Characteristics of Patients Undergoing Primary Percutaneous Coronary Intervention in the Southern Metropolitan Area of Barcelona After Implementation of the Infarction Code Program," *Revista Española de Cardiología (English Edition)*, 65, 911–918. [7]

HILLESTAD, RICHARD, J. BIGELOW, A. BOWER, R. M. FEDERICO GIROSI, R. SCOVILLE, AND R. TAYLOR. (2005): "Can electronic medical record systems transform health care? Potential health benefits, savings, and costs." *Health Affairs*, 24, 1103–1117. [2]

IMSS (2020): "Informe al Ejecutivo Federal y al Congreso de la Unión sobre la Situación Financiera y los Riestos del Instituto Mexicano del Seguro Social 2019-2020," . [3, 8]

INEGI (2017): "Encuesta Nacional de Empleo y Seguridad Social: Principales Resultados," Last accessed 10 March 2021, https://www.inegi.org.mx/contenidos/programas/eness/2017/doc/presentacion$_e ness_2 017.pdf$. [3]

Kellermann, A. L. and S. S. Jones (2013): "What it will take to achieve the as-yet-unfulfilled promises of health information technology," *Health Affairs*, 32, 63–68. [2, 6]

Lambert, L., K. Brown, E. Segal, J. Brophy, J. Rodes-Cabau, and P. Bogaty (2010): "Association Between Timeliness of Reperfusion Therapy and Clinical Outcomes in ST-Elevation Myocardial Infarction," . [7]

McCullough, J. S., S. T. Parente, and R. Town (2016): "Health information technology and patient outcomes: The role of information and labor coordination," *RAND Journal of Economics*, 47, 207–236. [6]

McNamara, R. L., Y. Wang, J. Herrin, J. P. Curtis, E. H. Bradley, D. J. Magid, E. D. Peterson, M. Blaney, P. D. Frederick, and H. M. Krumholz (2006): "Effect of Door-to-Balloon Time on Mortality in Patients With ST-Segment Elevation Myocardial Infarction," *Journal of the American College of Cardiology*, 47, 2180–2186. [7]

Menees, D. S., E. D. Peterson, Y. Wang, J. P. Curtis, J. C. Messenger, J. S. Rumsfeld, and H. S. Gurm (2013): "Door-to-Balloon Time and Mortality among Patients Undergoing Primary PCI," *New England Journal of Medicine*, 369, 901–909. [7]

Miller, A. R. and C. E. Tucker (2011): "Can Health Care Information Technology Save Babies? and RAND Corporation," *Journal of Political Economy*, 119. [6]

O.E.C.D (2019): "Health at a Glance." . [5]

O'Gara, P., Kushner, F.G., Ascheim, D.D., Casey, D.E., Chung, M.K., D. Lemos, J.A., Ettinger, S.M., Fang, J.C., Fesmire, F.M., Franklin, B.A., Granger, and C.B. (2013): "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." *Journal of the American college of cardiology*, 61, pp.e78–e140. [8]

Parente, S. T. and J. S. McCullough (2009): "Perspective: Health information technology and patient safety: Evidence from panel data," *Health Affairs*, 28, 357–360. [6]

Rathod, K. S., A. K. Jain, S. Firoozi, P. Lim, R. Boyle, J. Nevett, and M. C. D. etal. (2020): "Outcome of inter-hospital transfer versus direct admission for primary percutaneous coronary intervention: An observational study of 25,315 patients with ST-elevation myocardial infarction from the London Heart Attack Group." *European Heart Journal: Acute Cardiovascular Care 9*, 948–957. [3]

Scholz, K. Heinrich, S. K. Maier, L. S. Maier, B. Lengenfelder, C. Jacobshagen, J. Jung, and C. F. et al (2018): "Impact of treatment delay on mortality in ST-segment elevation myocardial infarction (STEMI) patients presenting with and without haemodynamic instability: results from the German prospective, multicentre FITT-STEMI trial," *European heart journal 39, no. 13*, 1065–1074. [4, 8, 16]

Wang, T. Y., B. K. Nallamothu, H. M. Krumholz, S. Li, M. T. Roe, J. G. Jollis, A. K. Jacobs, D. R. Holmes, E. D. Peterson, , and H. H. Ting. (2011): "Association of door-in to door-out time with reperfusion delays and outcomes among patients transferred for primary percutaneous coronary intervention." *Jama 305, no. 24*. [7]