Real-time Information and Organizational Performance*

Miguel Espinosa† Hyunjin Kim‡ Sergio Prada§

July 13, 2024

Abstract

Recent technological advancements have increasingly enabled data-driven decision-making across firms. While prior literature highlights the value of using more data in decision-making, there has been less insight on the impact of information *speed*. We examine how information speed influences organizational decision-making, leveraging data from a healthcare context. We analyze the effects of a technology that increased the speed of information by delivering real-time notifications of test results across 64,152 decisions made by 387 physicians. We find that faster information not only expedites decisions but also enhances their quality, resulting in improved organizational performance. These improvements stem from enabling decision-makers to acquire and learn from information more effectively. Thus, our findings indicate that investing in information speed can provide significant advantages from faster and better decisions.

Keywords: Data-driven decision-making, experimentation, technology, speed, information, healthcare

*We thank the valuable comments received by Medical Doctors Ludwig Albornoz, Nathalia Prado, Sergio Morales, Virginia Zarama, as well as Giada Di Stefano, Vibha Gaba, Harsh Jayant Ketkar, Myriam Mariani and the valuable technical assistance provided by Miyerlay Villada and Jaime Quintero, MD. Mateo Pedraza provided superb research assistance. Jordi Blanes provided valuable comments to an earlier version of this paper.

†Bocconi University, CEPR & CESifo, miguel.espinosa@unibocconi.it

‡INSEAD, hyunjin.kim@insead.edu

§Fundacion Valle del Lilli, Centro PROESA, Universidad Icesi, sergio.prada@fvl.org.co

1 Introduction

Recent technological advancements have enabled new opportunities to collect and leverage data across the organization, providing firms with more data to inform their decisions than ever before. This has led to changes in how managers and firms make decisions, leading them to rely more on data rather than intuition (Brynjolfsson and McElheran, 2016, 2019; Adner et al., 2019). Much recent work has highlighted the value of information for decision-making, showing that the availability and use of data improves firm decisions (Agrawal et al., 2019; Camuffo et al., 2020; Koning et al., 2022), and plays a role in driving performance differences across small and large firms alike (Nagaraj, 2022; Kim, 2023; Agarwal et al., 2023; Galdon-Sanchez et al., 2024).

While much focus has been placed on the *amount* of information and its value, another key implication of recent technological changes is the change in the *speed* of information: firms increasingly have access to real-time data to inform their decisions, and this increased speed may change how they make decisions, in addition to any additional information provided by the data.

However, there has been less insight into how this increased speed of information affects decisions in organizations. While we might expect that it should lead to *faster* decisions, how it affects the *quality* of decisions is more ambiguous. On the one hand, it may have little effect on the quality of decisions, leading to the same decisions simply made faster. On the other hand, it might change the decisions themselves by altering what information decision-makers decide to acquire and how they learn from that information. They may decide to obtain more or less information or become more or less targeted in the information they choose to acquire. Decision-makers may also learn differently from the same set of information if they consider it in real-time while actively working through their hypotheses, which may affect what they notice or the patterns they see.

In this paper, we propose that increasing the speed of information affects how quickly decisions are made and their quality, and provide empirical evidence from a healthcare context. We find that increasing the speed of information not only increases the speed of decisions but also enhances indicators of organizational performance, suggesting that it improves decisions overall. This appears to be driven by two key mechanisms. First, increasing the speed of information changes the information that decision-makers choose to acquire, leading them to collect more targeted information more efficiently. Second, it enables decision-makers to learn better from the information they gather. Our findings thus suggest that the speed of data may generate advantages from both faster and better firm decisions. This has implications for research on experimentation, suggesting that investing in information speed may help decision-makers improve their theories and develop better experiments (Camuffo et al., 2023; Agrawal et al., 2024; Camuffo et al., 2020). It also provides insights on how organizations may build competitive advantage based on speed advantages (Eisenhardt, 1989; Baum and Wally, 2003; Hawk et al., 2013), highlighting a new mechanism through which this can be built – via investments in the speed of information – and how it can improve decisions. More broadly, these findings highlight the importance of understanding not only what decisions are made but *how* they are made within organizations, especially in the age of data.

We examine the impact of an intervention that increased the speed of information by delivering real-time notifications on test results across 64,152 decisions made by 387 physicians serving 43,607 unique patients on *non-critical* cases in an Emergency Department (ED) of a major hospital.[1] This provided us with uniquely rich and detailed administrative data on a large number of decisions across a large number of decision-makers, and allowed us to observe the entire process of information acquisition (i.e., the tests they order), how they make their decisions based on this information (i.e., the length of time taken), and the performance outcomes of this decision for the organization (e.g., the costs incurred to deliver services, the quality of care, and patient satisfaction). The technology was installed in only one of the two adult wards in the hospital at a moment in time when no other changes were introduced in the organization, permitting the use of a difference-in-differences strategy (Chan, 2016).

We leverage a triple-differences strategy that additionally controls for potential seasonal effects to estimate the effect of this technology, which increased the speed of information provided to physicians. Before its implementation, a physician in our sample ordering a laboratory test for a patient was not automatically notified of test results when they became available. Instead, the physician had to navigate several screens in the internal software system to check manually whether the result was ready. This process required entering the physician's password and could not be delegated to a nurse. This friction meant that physicians did not check frequently to save time, a uniquely scarce resource in this setting, and thus experienced long lags in receiving information on the tests they ordered. In June 2022, a technology was installed in one ward, which visually notified physicians when test results were ready, thereby increasing the speed of information provided for the decisions

[1] Importantly, all critical cases arriving by ambulance requiring immediate physician attention (i.e., those with high mortality risk) were dispatched to a separate ward in this hospital. In such cases, the relationship between speed and organizational performance may be more directly linked and in part mechanical. We do not study this ward in this paper.

they made.[2]

As predicted, we find that the technology intervention increased the speed of decisions. Its introduction was associated with a significant decrease (13% in our most conservative estimate; approximately 103 minutes) in the length of stay of the average patient, which we interpret as indicating an increase in the speed of decisions. A leads and lags exercise indicates that the average length of stay evolved broadly similarly across the two wards in the months before June 2022, and then discontinuously decreased in the treated ward coinciding with the introduction of the technology.

We also find that this had broader effects on organizational outcomes, suggesting that decisions improved. We observe a decrease in the total costs incurred per patient episode, estimated at around 25% (about 365 US dollars, almost 1.5x the local monthly minimum wage in 2022). Despite faster and more efficient decisions, we find that the introduction of the technology also reduced patient hospitalization, without increasing the likelihood that the patient returned to the ED within 30 days. To the extent that these variables proxy for the health outcome of the patient, we conclude that the technology pareto-improved the quality of care for patients – suggesting that physicians made better decisions. Using responses from a random sample of patients to a survey conducted by the hospital, we also find an improvement in patient satisfaction.

We find that these effects appear to be driven by two key mechanisms. First, the technology changed the information that physicians chose to acquire, leading them to focus on

[2] For each ordered laboratory test, it showed the processing status, notifying physicians of whether the result was ready and whether the result was within pre-established ranges. These notifications were viewable by all physicians and nurses in the ward, but did not indicate specific test results, physician names, or patient names – only the patients' national ID numbers. Importantly, no notifications were physically sent to any physician device, and physicians still needed to log into the internal system to check the exact result manually.

more targeted information (i.e., more specialized tests), ultimately reducing the number of test results ordered. This accounted for about half of the gains observed in both the speed of decisions and the costs incurred. Second, increasing the speed of information appears to have improved how physicians learned from the information they acquired, enabling them to receive information at the time of decision to make better inferences. This was especially the case for uncommon decisions where they had to actively think through what information to acquire

Contribution to the literature We contribute to two strands of literature. First is the growing body of research on data-driven decision-making, showing the value of information for strategic decisions (Brynjolfsson and McElheran, 2019; Camuffo et al., 2020; Koning et al., 2022; Nagaraj, 2022; Kim, 2023; Kim et al., 2024). Our findings suggest that in addition to the amount of data, the speed of information is an important determinant of how decision-makers learn to improve strategic decisions. Our study also highlights two key mechanisms that determine how decision-makers learn to improve strategic decisions: first, their choice of what information to acquire, and second, their ability to learn from the information acquired.

Second, our paper contributes to research on speed or time as a source of competitive advantage. Much work has emphasized the importance of speed for organizational performance and competitive advantage (Stalk, 1988; Eisenhardt, 1989; Stalk Jr and Hout, 1990; Forbes, 2005; Hawk et al., 2013; Teece et al., 1997; Helfat et al., 2009), through a first-mover advantage (Makadok, 1998), a series of temporary advantages (Garud et al., 1998), or improved learning via more interactions with the environment (Eisenhardt, 1989; Mosakowski, 1997). This literature has generally conceptualized speed as an advantage in competition, for example by enabling firms to more rapidly respond to customer demand and realize revenues from investments relative to competitors (Stalk, 1988; Hawk et al., 2013; Pacheco-de Almeida et al., 2015).[3] Much of this literature has also been theoretical, qualitative, or correlational – providing valuable insights but making it difficult to disentangle the impact of speed from other related changes such as flexibility (e.g., just-in-time production) or better management practices. In this paper, we highlight a decision-based advantage from speed and identify a novel lever through which organizations can increase decision speed – improving the speed of information. We also provide evidence that suggests that the speed of information *causally* enables better strategic decisions and organizational performance, beyond decision speed alone.

2 Theoretical framework

In this section, we first examine the role of information in firm decisions and performance. Next, we contend that in addition to the quantity of information, the speed of information plays a key role in firm decisions. Finally, we present our hypotheses on how the speed of information affects the speed and quality of decisions in organizations.

2.1 The role of information in firm decisions and performance

Information – on competitors, customers, suppliers, and internal operations – is a crucial input to firm decisions. From the literature on evidence-based management (Pfeffer and Sut-

[3] A key exception is Eisenhardt (1989), which focuses on how speed affects decisions.

ton, 2006; Barends and Rousseau, 2018) to more recent work on data-driven decision-making (Brynjolfsson and McElheran, 2019), growing research has shown that using information and data-driven processes is a key driver of firm decisions and performance differences across firms in entrepreneurial (Camuffo et al., 2020; Koning et al., 2022), innovation (Nagaraj, 2022), and competitive strategy contexts (Kim, 2023). Complex decisions in organizations require decision-making under uncertainty, which data can help inform (Agrawal et al., 2019; Kim et al., 2024).

Moreover, research on experimentation has highlighted that taking actions to acquire information is a core driver of how organizations learn to make better decisions (Ries, 2011; Eisenmann et al., 2012; Blank, 2013; Kerr et al., 2014; Gans et al., 2019; Camuffo et al., 2020; Leatherbee and Katila, 2020; Koning et al., 2022). While much of this work has focused on the entrepreneurial context, recent approaches in strategic decision-making have highlighted parallels outside entrepreneurship. Applying a real options approach to strategy emphasizes how initial investments allow firms to collect signals about possible options (Adner and Levinthal, 2004). A "Mendelian" view of how executives operate highlights the role of intentionality in generating options, testing them through "experiments", and making a choice (Levinthal, 2017). Across this literature, including in entrepreneurial strategy, experiments generally refer not to formal experimentation, but more broadly to actions designed to yield the gathering of information to inform a choice. For example, this may entail interviewing customers or releasing a prototype, as well as launching an A/B test.

However, much of this research has focused on the value of acquiring *more* information (Kim, 2023; Koning et al., 2022), rather than on *how* decision-makers choose to acquire information. Research on evidence-based and data-driven decision-making has largely focused on the availability of data and its use (e.g., Brynjolfsson and McElheran (2016)), providing evidence that more information can be valuable. However, it has yielded less insight on key decisions that organizations make on how to acquire information, such as the timing of information acquisition or the validity of the method chosen. Similarly, research on experimentation has generally focused on whether information is acquired as a binary action and emphasized the importance of complements such as specifying theories (Camuffo et al., 2020; Agarwal et al., 2023), leaving the design of the actual "experimentation" process of information acquisition as a black box.

2.2 Speed of information as an organizational lever

In particular, one key dimension that has been overlooked is the *speed* of information acquisition. This is somewhat surprising, given that the excitement around "big data" in management highlights three defining attributes – the "volume" of data available, the "velocity" of data creation, and the "variety" of data types that organizations can use (McAfee et al., 2012). Yet while there has been much research on how the volume and variety of data (e.g., unstructured digital exhaust from sensors, social media, and clickstreams) impact firm decisions, the implications of information speed have been less studied.

While these attributes can often come as a bundle, increased speed of information is distinct from the availability of data or the costs to acquire it, which have been studied extensively both theoretically and empirically (e.g., see Bloom et al. (2014) and Goldfarb and Tucker (2019) for reviews). For example, net neutrality does not affect the amount of information being transmitted, but impacts the speed at which the same information is delivered, ensuring that one company cannot pay to send the same amount of data to the same customer at a faster speed. Similarly, internet-enabled applications like WhatsApp or Skype lower the cost of transmitting information relative to telephones, but largely without changing the speed of information.

Moreover, organizations often invest in the speed of information acquisition. The importance of real-time data has been highlighted by managers across industries for its potential to improve high-stakes decisions. For high-frequency trading, banks invest in cable innovations and server proximity to the exchange for faster data transmission and trade execution by milliseconds to outrun competition (Osipovich, 2020). Similarly, companies across industries invest in data processing architecture to avoid being saddled with old infrastructure, which can introduce delays in providing information on data-generating events (Guagenti, 2019). In addition, many recent business innovations rely on information speed at their foundation. Online platforms that rely on matching such as ride-hailing or delivery would not be able to function without real-time data, and part of the early value of large language models (LLMs) such as GPT-3, Claude, and LLaMA stemmed from their ability to provide information from the internet more quickly, speeding up the process of information acquisition. These investments are not intended to change the amount or variety of information for decision-making, but to increase its speed.

2.3 The impact of information speed on decisions

The primary reason proposed for why organizations invest in information speed is that this can lead to speed-based advantages. Naturally, having information in real-time or close to it has been seen to enable agility in decisions relative to competitors, providing insights on the market before others make a move (McAfee et al., 2012). For example, hedge funds and investment banks use satellite data to count cars in retailers' car parks ahead of corporate earnings releases, detect oil storage tanks across the world to gauge movements in oil prices before they happen, or identify events like hurricanes or wildfires before reports (Hawser, 2022). Similarly, many businesses highlight how real-time customer data enable them to respond more quickly to customers and identify changes in demand (Garduno, 2022).

This insight is echoed in the literature on speed advantages, which suggests that executives who attend to real-time information can react and decide more rapidly (Eisenhardt, 1989). Research on speed-based advantages suggests that reaching the same decision faster can alone provide competitive advantages by enabling faster competitive moves: firms can exploit opportunities and capture customers before their competitors (Hawk et al., 2013; Pacheco-de Almeida et al., 2015; Stalk, 1988), strengthen commitment from their stakeholders (Langley, 1995; Pfeffer and Sutton, 2000), and learn more quickly by making more decisions (Eisenhardt, 1989). While much of this literature has been theoretical, correlational, or qualitative in nature, often based on a few case studies that have yielded at times contradictory results (e.g., Perlow et al. (2002)) and hampered causal inference, it raises the possibility that faster information acquisition may lead to decision speed, which can provide performance advantages relative to competitors.

This leads us to our first hypothesis, which suggests that one way to gain a speed advantage is by investing in information speed.

Hypothesis 1*: Increasing the speed of information acquisition leads to a faster decision, reducing the length of time to reach a decision.*

In many cases, this relationship may be relatively straightforward: receiving information faster can allow a decision-maker to reach a decision more quickly by being able to consider the information sooner.

However, what is much less straightforward is how the increased speed of information might affect the quality of decisions – even without the advantages of decision speed relative to competition. While much research on speed advantages implicitly assumes that receiving information more quickly will lead to the same decisions being made, simply faster, we argue that increased speed may in fact change and improve decisions.

First, we hypothesize that with timely information, decision-makers can identify more relevant and targeted information, which may allow them to ultimately require less information overall. Timely information may enable decision-makers to be more adaptive in their information acquisition approach: they can make sequential decisions to learn from the early information they acquire to inform whether and which additional information they need, rather than seeking as much information as possible at once in anticipation of a long delay. Research on sequential and Bayesian experiments suggests that adaptive information acquisition strategies can alter the course of experiments by improving their relevance and ensuring that efforts are concentrated on the most promising lines of inquiry (e.g., Berry (2004); Mao and Bojinov (2021); Bojinov and Gupta (2022)). For example, physicians may order several potentially relevant patient tests at the outset in anticipation of a delay, but if none of those bear out, they may require many more additional tests to determine promising paths to diagnosis. In contrast, if results arrived quickly, they might be able to order fewer tests and learn from early test results to determine which additional tests might be most informative to make a diagnosis. This set of information acquisition choices would be more efficient and effective, enabling them to order fewer tests that are more targeted to make the diagnosis. Similar patterns may apply in other contexts, such as in product development. For example, online contexts can generally enable faster information speed in collecting customer feedback compared to offline contexts, which has led many technology companies with online products to launch smaller early experiments that can provide targeted data to inform subsequent decisions on whether to build a new product feature.[4]

Second, information speed may improve how decision-makers learn from the information. Research in cognitive science suggests that the timing of stimuli affects what decision-makers notice and attend to at a time, due to cognitive constraints that restrict our span of memory and ability to process information (Miller, 1956; Lachman et al., 2015). This also relates to the concept of bounded rationality, that a decision-maker does not have enough cognitive bandwidth to consider all relevant information – which has been seen as a key binding constraint to strategic decision-making in the management literature (Simon, 1991). Similarly, having more considerations on one's mind has been shown to decrease cognitive ability, as tasks compete for limited mental resources (Mani et al., 2013). These findings suggest that increasing the speed of information could enable decision-makers to receive information at a more optimal time when they are holding all details of the decision in their memory without interruption in their attention. Instead of receiving information at a later time when other decisions have entered one's mind and contextual details or possible hypotheses forgotten, timely information may provide decision-makers with insights at the point of consideration, enabling them to make better inferences and ultimately better decisions.

[4]It is worth noting that there are many other differences between offline and online contexts, including the lower cost of acquiring information, which also may increase the total amount of information acquisition as well as its efficiency (Koning et al., 2022).

For example, in the context of physicians who perform complex and high-stakes decisions requiring cognitive capacity, one primary source of cognitive load is the number of patients, especially when they exhibit a wide variation in health conditions to be diagnosed, as is often the case in an Emergency Department (Shanmugam, 2020). When information arrives slowly and the hospital is busy, a physician may have to switch to tending to another patient 2 while waiting for test results on patient 1 to arrive, which would require switching back to patient 1 when the results arrive. The physician may be less able to make inferences from patient 1's test results because she has had to switch back to this patient, making it more difficult to hold all relevant details in her memory and process the information correctly. In contrast, if patient results were delivered faster, she would not have to switch to patient 2 – instead receiving patient 1's test results as she actively considers the patient's symptoms. This may allow her to notice that symptom X does not fit the pattern of diagnosis A, or remember that the patient had Y symptoms which allows her to form the hypothesis that it may be another category B of diagnoses entirely. As a result, she would not erroneously order tests for diagnosis A, but instead make the correct inference that she must consider diagnoses in category B.

This leads us to our second and third hypotheses:

Hypothesis 2: *Increased speed in information results in improved decisions as measured by organizational outcomes.*

Hypothesis 3: *This improvement in decisions stems from how decision-makers acquire and learn from information.*

(a) More effective information acquisition: *Information speed leads decision-makers to collect less information that is more targeted.*

(b) Better learning from information: *Information speed leads to better learning from information by receiving it at the time of decision.*

In the healthcare context, ***Hypothesis 3(a)*** indicates that increasing information speed should result in changes in the information that physicians choose to acquire, leading them to acquire fewer laboratory tests that are more targeted and specific. It also implies that decision improvements should stem from patient cases that require information acquisition (i.e., ordering tests). ***Hypothesis 3(b)*** suggests that information speed should lead to decision improvements, especially during busy times when physicians may experience higher cognitive load due to potential switches to another patient case, which can hinder processing and learning from information. It also implies that improvements in decisions should be especially likely for uncommon cases involving rare conditions that may require more cognitive capacity to learn from the information and think through potential hypotheses.

The alternative null hypothesis to ***Hypothesis 2*** is what is implicitly assumed by much of the current literature: that decisions remain the same and are simply made faster. The alternative hypotheses to ***Hypothesis 3(a)*** are that increasing the speed of information either has no effect on information acquisition choices or leads decision-makers to collect more information that is less relevant for their decisions. The alternative hypotheses to ***Hypothesis 3(b)*** are that information speed either hurts or has no effect on decision quality during busy times or for uncommon cases imposing higher cognitive load.

In the following sections, we evaluate whether increasing the speed of information not only leads to faster but also better decisions that improve organizational performance. After establishing this relationship, we explore the possible mechanisms of why faster information might lead to improved decisions and performance. Specifically, we investigate whether and how the speed of information affects the information decision-makers choose to acquire and how they learn from that information.

3 Empirical setting

We leverage evidence from a healthcare context to explore how information speed affects decisions and organizational performance. We first discuss the empirical requirements of exploring this question and how we address them, and then describe in detail the empirical context and the technology intervention that increased the speed of information.

3.1 Empirical requirements

Empirically exploring how information speed affects strategic decisions and organizational performance imposes many requirements. First, it requires observing a large number of complex or high-stakes decisions made by a large number of key decision-makers, rather than those that are operationally automated using pre-defined rules such as manufacturing production systems or marketing outreach. Studying such decisions enables us to understand how providing real-time information affects how decision-makers acquire and learn from information and the resulting choices that they make. Moreover, given that a key feature of strategic decision-making is decision-making under uncertainty, a large sample of decisions is required to evaluate whether *in expectation* decisions improve performance, since observing the outcome of a single decision is not indicative of its quality. Similarly, observing a large number of decision-makers on a similar set of decisions is important to explore whether any effect might be particular to a single decision-maker or differential across decision-makers.

Second, we need to observe the full process of decision-making, including what information decision-makers choose to acquire and how they make their decisions based on this information – including their time to decision and the performance outcomes of decisions for the organization. This is often not easy, as in many organizations high-stakes decisions are not fully documented or measured in timing, and it can be difficult to observe the nature and attributes of the information decision-makers choose to acquire, which is generally sensitive, ad-hoc, and idiosyncratic.

Third, we require a substantial and plausibly exogenous change in the speed of information acquisition. This requirement is crucial to tease apart information speed from other changes like better management practices or the amount of information, to determine the causal impact of increasing information speed.

To address these challenges, we leverage a unique opportunity to analyze detailed data from inside a real organization in the healthcare industry, which provides several advantages. First, this data provides us with rich insights on decisions at scale. During our sample period (March-October for 2019 and 2022), 387 physicians in the Emergency Department received and made over 64,152 decisions across 43,607 unique patients. For each physician, we observe the full process of information acquisition. We observe baseline conditions for each decision: the physician's experience as well as when and which patients were allocated to her, including their initial health conditions at the time of the arrival (triage, vital signs). We observe the choices each physician made on information acquisition: how many and which laboratory tests were ordered by the physician, and when these tests were ordered. Unlike many hospitals that outsource to third-party labs, this hospital conducts diagnostic lab work in its own state-of-the-art lab. Common tests include complete blood counts (CBC) for detecting infections and anaemia; chemistry profiles for assessing enzymes, electrolytes, and sugar levels, useful for diagnosing heart attacks, diabetes, dehydration, and kidney problems; and urine tests for detecting kidney issues, including stones.

We also observe how quickly the decision was made, approximated by the patient's length of stay in each case. Finally, we observe key organizational outcomes of decisions made: the total cost incurred, proxies of the quality of treatment (e.g., hospitalization and whether the patient returned to the Emergency Department within 30 days), and patient satisfaction.[5]

Finally, our partner organization introduced a technology during our sample period that provided immediate notifications of laboratory test results to physicians. This technology was implemented in only one of its two ER wards at the time, providing substantial and exogenous variation to the extent that this technology effectively increased the speed of information acquisition.

3.2 Empirical context

The Emergency department Our study takes place in the Emergency Department of the Fundación Valle del Lili (henceforth FVL) Hospital. The FVL hospital is a general teaching hospital located in Cali, Colombia, ranked 162nd in the world in the 2024 edition of The World's Best Hospitals (Newsweek, 2024). In 2021, the hospital included 680 beds and 20 operating rooms and had 724 physicians. With these resources, the hospital processed around half a million outpatient visits and 36,000 hospital discharges.

The FVL Emergency Department operates similarly to those in other hospitals around

[5]The cost variable encompasses all resources utilized and billed to the third-party payer from the patient's admission to the emergency room (ER) until discharge from the hospital. This includes drug expenses, laboratory tests, consumables, and physician honoraria.

the world, with the important proviso that the ward to which patients are directed depends on their insurance status. Upon arrival, potential patients are received by administrative staff, who check for insurance eligibility to be admitted, and then by a nurse. An important caveat is that all patients – independent of insurance – who arrive by ambulance after a car accident, a heart attack, or a similarly critical condition with high mortality risk, skip this step and are sent directly to the resuscitation room. Once they are stable, they are sent to the Intensive Care Unit. Similarly, any patients with no triage level – because their condition does not require seeing a physician – are also dismissed. The remaining patients with conditions that require physicians but are less urgent or high-risk are then triaged and assigned to one of two Emergency Department wards depending on their triage level and insurance status, as follows. Patients with standard national insurance coverage and triage levels 1-3 are sent to the 'regular' ward. Patients with additional private insurance coverage and triage levels 1-5 are sent to the 'private insurance' ward.[6]

Upon arrival to each ward, patients wait in front of the consulting rooms and join a virtual queue, in which the queue order depends on both arrival time and triage level. The patient at the front of the queue is then matched with the next 'initial consultation' physician that becomes available (there may be several such physicians working in parallel). In the consulting room, this physician gathers additional information, potentially orders laboratory tests, and performs an initial diagnosis.[7] The patient is then sent to a bed for observation and is put under the care of a different physician. This attending physician

[6]The triage system in an Emergency Department (ED) prioritizes patients based on the severity of their condition, ensuring that those needing immediate medical attention receive it first. Triage level x-1 requires more urgent and quick attention than triage level x.

[7]Although physicians may order other tests, such as X-rays, our study focuses solely on laboratory tests because the screen only affected the speed of obtaining laboratory test results.

reviews the information, periodically observes the evolution of the patient, potentially orders more laboratory tests, and incorporates the information from the test results when these become available and are communicated to her. At regular intervals, the attending physician decides between: (a) keeping the patient in the ward for longer, (b) discharging him, and (c) admitting him to the non-emergency wing of the hospital (hospitalization).

Increasing the speed of information acquisition Before the installation of the technology, attending physicians had to manually log into the internal software system and navigate a number of screens to check whether a laboratory test result had become available. Searches were individual, in that a physician inquiring about the result of a specific patient was not alerted if the result of a different patient had become available. This process could not be delegated to a nurse, as it required entering the physician's password. The system imposed unnecessary burdens on physicians to check multiple times and resulted in substantial delays in information acquisition.

In 2022, FVL decided to alleviate this bottleneck by providing physicians with immediate notifications on the status of each laboratory test. In partnership with a provider of software services, and in consultation with the authors of this study, this technology was implemented only in the private insurance ward, but not in the regular ward. The status of test results could be visually consulted at all times by any nearby staff member but was hidden from patients and relatives. For each laboratory test ordered for each patient, the technology displayed the type of test (e.g. glucose, hemoglobin, etc.) and its availability.[8] Learning

[8]Cells were empty if the corresponding test type was not part of the order set, and filled with a circle if it was. Circles were white if test results were not yet available; blue if they were in the process of validation; green if results were available and were within pre-established standard intervals; yellow (i.e. concerning) or red (i.e. critical) if results were available and outside these intervals.

the actual numerical values of the test results required logging into the system with the physician's password.[9] Importantly, there were no active notifications that were sent to any physician: test result availability was only displayed visually to inform physicians that they could log in and view the results.

This technology was installed in the third week of June 2022. Over the last two weeks of June, physicians were informed and trained about its use. For this reason, we take July 2022 as the first month in which the technology was active and used by physicians.

4 Empirical strategy and data

In this section, we outline our empirical strategy and discuss the rationale behind the use of a triple-differences specification. We also explicitly outline our method for testing the parallel trends assumption and provide the main descriptive statistics of our data. Finally, we present arguments supporting the validity of our research design.

Differences-in-differences Our empirical strategy leverages a differences-in-differences (DiD) specification. Cases assigned to the private insurance ward, where the technology was implemented from June 2022 onwards, represent the treatment group. Cases assigned to the regular ward, where the technology was never set up, represent the control group. Specifically, a baseline difference-in-differences model would estimate:

$$y_i = \beta(Private_{w(i)} \times Post_{t(i)}) + \alpha_{d(i)} + \theta_{in(i)} + \pi_{t(i)} + \gamma'\mathbf{X_i} + \epsilon_i \tag{1}$$

[9] Throughout our sample period, the technicians in the laboratory would typically phone the ED immediately if the test results were in the critical range. This custom did not change after June 2022.

where y_i is an outcome (such as length of stay) of case i, $in(i)$ indexes the ward to which patient i is assigned, $d(i)$ indexes the physician allocated to patient i, and $t(i)$ indexes the exact hour (i.e. date and hour of day combination) in which patient i arrived. The model controls for physician $\alpha_{d(i)}$, insurance company $\theta_{w(i)}$ and hour $\pi_{t(i)}$ fixed effects, as well as patients' pre-determined characteristics $\mathbf{X_i}$ (patient age and gender, triage level, main diagnosis and patient vital signs on arrival to the ED).[10] The parameter β captures the average differential outcome for cases assigned to the private insurance ward following the introduction of the technology.

Triple-differences strategy In the context of Emergency Departments, the exploitation of organizational changes to one hospital ward while using a different ward as a control group in a DiD strategy was pioneered by Chan (2016).[11] The identification assumption in this type of strategy is *not* that the expected outcomes across the two wards would have been similar in the absence of the treatment, an assumption that would clearly be violated in our setting. Instead, identification requires that the average outcomes across the two wards would have evolved similarly in the absence of the introduction of the technology.

A challenge in our setting is that, according to our discussions with FVL administrators and physicians, the introduction of the technology potentially coincided with seasonal changes in the composition of cases. Specifically, it may be that healthier patients (even after controlling for patient characteristics) may reach the private insurance ward in the summer months, relative to the winter months and to the regular ward.[12] To alleviate this concern,

[10]Instead of controlling for the ward to which the patient is assigned, we control more finely for the detailed insurance company of the patient as the insurance company fully determines the ward.

[11]We follow Chan (2016) in clustering the standard errors at the physician level.

[12]Alternatively, the number and composition of the medical staff present in the two wards may differ across the seasons, in a way that is not controlled by the physician fixed effects included in the regression. We

our main estimating strategy is a triple-differences model comparing the months after June in the private insurance ward in 2022, relative to the regular ward and to 2019.[13] Specifically, we pool the 2019 and 2022 March-October months together in the sample and use as the main independent variable of interest the triple interaction between $(Private_{w(i)} \times Post_{t(i)})$ and a year 2022 dummy. The model becomes:

$$y_i = \beta(Private_{w(i)} \times Post_{t(i)} \times 2022_{t(i)}) + \alpha_{d(i)} + \theta_{in(i)} + \pi_{t(i)} + \gamma'(\mathbf{X_i} \times 2022_{t(i)}) + \epsilon_i \qquad (2)$$

In this triple-differences model, all the control variables (i.e., $\mathbf{X_i}$) are interacted with the year 2022 dummy to capture different evolution in the baseline characteristics of the patients.[14]

The main tables below report the results when the continuous (Length of Stay and Costs) and count measures (number of laboratory tests) are log-transformed. We do so to minimize the impact that outliers can have on our results. All our results are consistent and qualitatively similar if instead of using the log-transformation, we use the Inverse Hyperbolic Sine (IHS) transformation.

Event study analysis The standard test of the identification assumption in the differences framework is the evaluation of potentially differential pre-trends. We evaluate these pre-

have no anecdotal evidence that this is indeed the case, but it might be a potential concern.

[13] We chose the year 2019 as it is the last pre-COVID year. In 2020 and 2021 multiple changes to the internal organization of the ED (including the temporary elimination of the private insurance ward) make comparisons difficult. If instead, we choose 2018 instead of 2019, we obtain very similar estimates.

[14] A potential threat to the identification of our results is that the characteristics of the patients or physicians changed differentially across wards. Figure A.1 shows the coefficient estimates of our triple-difference model on different observable characteristics of the patients and physicians. The Figure shows that most of these interaction terms are not statistically different from 0, which provides evidence of the validity of our research design. Two variables show some negative and significant effects, gender (male) and age of the patient. This indicates that there is an increase in the fraction of younger men in the pool of patients in the private ward after the introduction of the technology. To deal with any potential changes in the composition of the pool of patients, we control explicitly for these variables below, so that all the results we present are robust to the potential change in the characteristics of the pool of patients.

trends using the following leads and lags model:

$$y_i = \sum_{j=-K...-1}^{1...K} \beta_j(Private_{w(i)} \times Monthj_{t(i)} \times 2022_{t(i)}) + \alpha_{d(i)} + \theta_{in(i)} + \pi_{t(i)} + \gamma'(\mathbf{X_i} \times 2022_{t(i)}) + \epsilon_i \quad (3)$$

where $\hat{\beta}_{-K}, ..., \hat{\beta}_{-1}$ capture the estimated effects of being assigned to the private insurance ward in the K months leading to the introduction of the technology, and $\hat{\beta}_1, ..., \hat{\beta}_K$ capture the corresponding effects for the K months following the introduction in June 2022.[15]

Descriptive statistics Our main analysis sample comprises eight months centered around the introduction of the technology in June 2022, and their equivalent in 2019. The $64,152$ cases in our sample include $43,607$ distinct patients cared for by 387 distinct physicians. Table 1 displays summary statistics for the main variables in the study.

—— *Insert Table 1 Here* ——

5 Information speed and time to decision

In this section, we display the results of testing Hypothesis 1, which predicts that increasing the speed of information leads to a faster decision. We approximate the length of time to reach a decision with the patient's length of stay, an important measure of organizational performance for hospitals more generally (Chan, 2016, 2018; Chan and Chen, 2022). We also provide empirical evidence demonstrating that our research design seems to be valid, robust, and correctly identified.

[15]Note that our empirical specification is not affected by recent criticisms about DiD designs (de Chaisemartin and D'Haultfeuille, 2017; Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021). First, treatment is not 'fuzzy' as defined in de Chaisemartin and D'Haultfeuille (2017) because no case is treated in the control group. Second, the treatment affects all the (treated) cases simultaneously and the private insurance ward remains treated for the remainder of the sample period. This rules out the concerns related to staggered treatment designs (Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021).

Baseline results Table 2 displays the baseline results from running our triple-differences strategy according to equation 2. We start in Column 1 with a simplified model, which only controls for a post dummy and a private insurance ward dummy (both interacted with the year 2022 dummy). In Columns 2 and 3 we then sequentially introduce insurance status and hour-fixed effects, as well as (initial consultation) physician-fixed effects. From column 4 onwards, we add patient controls. Column 4 additionally winsorizes the top and bottom 1% of the length of stay distribution. While log-transforming this dependent variable should have alleviated the strong skewness of the length of stay distribution, winsorizing the top part of the distribution contributes to reassuring us that the baseline estimates are not disproportionately due to extreme positive values. We find that the introduction of patient controls and winsorizing the distribution has a strong effect on the estimate, decreasing it in absolute value from $-.35$ to $-.16$. In column 5, we drop Triage 4 and 5 cases from the sample without winsorizing the distribution. Because these cases are only present in the private insurance ward, dropping them from the sample increases the homogeneity of the average case across the two wards, but substantially decreases our sample size. Finally, column 6 adds back the Triage 4 and 5 cases without winsorizing the distribution, and the treatment estimate remains broadly similar to column 5, and is more conservative than winsorization in column 4. Given this, we take this model as our baseline estimate.[16] The reduction of 13% represents a decrease of about 100 minutes with respect to the mean (the average episode lasts about 13 hours).

—— Insert Table 2 Here ——

To understand better the magnitude of the estimates and provide further validation to our

[16] We obtain similar results if we winsorize the distribution of the length of stay in this column.

triple-differences model, Table A.1 displays the baseline results from estimating Equation (1). We find consistent results. The DiD model centered around July 2022 suggesting in Column 1 that the introduction of the technology is associated with a 25% decrease in the average length of stay. In Column 2, we repeat the estimation of (1) but in the 'placebo' year of 2019, in which no technology was introduced at any point. We find that the post-June period was associated with a decrease in length of stay of around 11%. While the decrease in the post-June months is much smaller in 2019 relative to 2022, it is still statistically significant. This suggests that there might be seasonal effects in the differential composition of patients arriving to the private insurance and regular wards. This confirms that a triple-differences model is more likely to be appropriate in our setting.

Leads and lags analysis We display in Figure 1 the estimates of (3). We do not find a significant differential effect of being assigned to the private insurance ward in the months leading to the introduction of the technology. In the first full two-month period after this introduction, a discontinuous decrease in length of stay of around 35% is apparent in the figure. Overall, we interpret the evidence in Figure 1 as largely supportive of the main identification strategy in the paper.

Furthermore, Rambachan and Roth (2023) provides insight on how to conduct robust inference in designs that use difference-in-differences designs even if the assumption of parallel trends' assumption may be violated. The idea is that we can estimate how large the post-treatment violations of the parallel trends have to be to make the design invalid. Figure A.3 conducts this robust inference and shows that the violation of the parallel trends assumption has to be very large (larger than it could be, given Figure 1) for our suggested effects to be invalid. Given the evidence of Figure 1 and A.3, we think that our design is valid as there is sufficient evidence to argue that the two emergency department wards were behaving similarly before the intervention but not after.

—— Insert Figure 1 Here ——

In summary, these findings provide evidence in support of Hypothesis 1, showing that increasing the speed of information acquisition leads to faster decisions. This effect may alone in some cases provide advantages for organizations, enabling them to make decisions before their competition, and suggests that one key lever through which organizations can realize speed advantages is through investing in the speed of information acquisition.

In the next section, we provide empirical evidence for our other two hypotheses.

6 Information speed and organizational outcomes

In this section, we display the results of testing Hypothesis 2 on the effect of the speed of information on different organizational outcomes (costs, quality of care, and patients' satisfaction). We also provide additional empirical evidence on the assumptions necessary to validate the robustness of our identification strategy.

Main results In Table 3, we examine the impact of increasing information speed on indicators of organizational performance. Column 1 of Panel A examines an outcome variable that indicates the total costs associated with diagnosing a specific case. We find that this total cost variable decreased by around 25% following the introduction of the technology. Given that the average cost is about 1.4K US dollars, this represents a decrease of about 365 US dollars, approximately 1.5 times the local monthly minimum wage in 2022. These results are robust to winsorizing the cost variable. For instance, when we winsorize at 95% or 90%, the coefficient is still negative and significant at 1%, estimated at 24% and 22%, respectively.

—— *Insert Table 3 Here* ——

In the remaining columns of Table 3 Panel A, we display the effects of the technology on organizational outcomes related to the quality of care. In Column 2 we find a large effect on the likelihood that the patient is hospitalized, as opposed to being discharged home. The decrease in this likelihood is around 7 percentage points, which represents around 27% of the unconditional likelihood. To the extent that admission to the hospital represents an acknowledgment that the patient has not improved sufficiently during her stay at the Emergency ward, we can conclude that increasing the speed of information through the introduction of the technology improved patient outcomes.[17] Second, we find in Column 3 of Table 3 Panel A that this decrease in hospitalization happened without increasing the likelihood that the patient would return to the ED in the next month. The estimate is close to zero and is statistically insignificant, suggesting a safe discharge and thus an overall improvement in the quality of care.

The leads and lags figures for these outcome variables can be found in Figure 1. For all outcomes, the graph shows no significant differences between the private insurance ward and the other ward in the months leading up to the introduction of the technology, providing further support for our main findings. Moreover, Figure A.3 shows that the potential for violation of the parallel trend assumptions that would invalidate the research approach is

[17] Conditional on two patients with the same initial condition (i.e., same initial vital signs, triage, entry time, physician), hospitalization is likely to reflect a worse treatment for the condition than being discharged home since it means that the patient was not able to recover sufficiently.

much larger than they are according to Figure 1, providing additional support to the validity of our econometric design.

Patients' satisfaction We additionally find that the introduction of the technology improved patient satisfaction with the care provided in the private insurance ward, relative to the regular ward (Table 3 Panel B). This may have been driven either by the decreased time taken to resolve their case or by the increased quality of care.

Our measures of patient satisfaction are based on a survey sent to a randomly-selected subset of patients. We focus on three responses to the survey: (1) whether the patient thought that the medical staff displayed the right attitude in the provision of care, (2) whether the patient thought that the physician complied with good medical practices, and (3) whether the patient believed that the physician was good at answering questions and addressing potential concerns.[18] Unfortunately, we only have these survey results for the year 2022 and for a sample size of fewer than two thousand observations. As a result, the specification for these variables is a DiD model that follows equation 1 (with coarser time effects) and results are noisier.

Panel B of Table 3 displays the results of these estimations. We find that the introduction of the technology had positive effects on patient satisfaction for all three measures. In terms of magnitude, the improvement on the attitude question is .2, which represents 37% of the .54 sample standard deviation. The increase in compliance and reported willingness to answer questions are slightly smaller at around 26% and 31%, respectively. We also use as a dependent variable the average of the three questions and find qualitatively similar results.

[18]Specifically, the questions in Spanish are ¿Cómo califica la atención médica? En terminos de: (1) Actitud de Servicio, (2) Cumplimiento en la cita, (3) Información y respuesta a sus inquietudes.

The effects are large in magnitude, which illustrates how faster and improved decisions resulting from increasing information speed can have a meaningful impact on the way that patients feel about the hospital service.

In Figure A.2, we plot the estimated leads and lags from equation (1) of patient satisfaction. We find that patient satisfaction is not trending in any direction before July 2022, after which there is a meaningful improvement in all three measures as well as the average. Despite some noise in the estimates, Figures A.2 and A.3 (Honest DiD for the average of the three patient satisfaction questions) suggest that technologies altering information speed can meaningfully impact patient satisfaction.

Taken together, the results in this subsection show that increasing the speed of information acquisition is associated with improved indicators of organizational performance: lower costs, higher quality of care, and higher patient satisfaction.

7 Evidence on mechanisms

In this section, we provide suggestive evidence for Hypothesis 3: the mechanisms through which the speed of information might improve decisions. We focus on two key channels: changes in information acquisition and learning from data. We then explore evidence for alternative mechanisms.

7.1 The information acquisition mechanism

First, we examine whether increasing the speed of information led to changes in information acquisition choices by decision-makers, following Hypothesis 3(a). In Column 1 of Table 4, we replicate our baseline specification to examine whether physicians changed the number of laboratory tests that they ordered. We find a precisely estimated negative coefficient: on average, the number of tests ordered decreased by 10% following the introduction of the technology. This finding suggests that increasing the speed of information led to more efficient information acquisition choices, decreasing the amount of overtesting.

—— *Insert Table 4 Here* ——

We confirm this finding in Figure 1, where we find that the number of tests ordered remained broadly unchanged in the months leading up to the introduction of the technology, and then decreased around 20% in August 2022, consistent with the equivalent figure for length of stay, as well as other organizational performance outcomes (Panels A, B, and C). The similarity in the evolution of these outcomes suggests that the decrease in the number of tests may have been a key mechanism enabling improved decisions.

We find that the largest reduction in the number of tests stemmed from the end of the decision, suggesting that earlier tests may have been effective in finding a promising path to diagnosis. Within the sample of cases where tests were ordered, we cut the length of stay into quartiles for each case. Columns 4-7 in Table 4 show that the reductions in the number of tests ordered stem mostly from the last quartile. This reinforces the idea that physicians were able to make more efficient information acquisition choices earlier on, decreasing the need to order additional tests at the end of their decision period.

Specialized and generic tests Next, we focus on classifying tests by type: specialized and generic. Generic tests are those that are frequently used across a wide range of conditions. For instance, Complete Blood Count (CBC) measures the levels of white and red blood cells as well as platelets. These tests are very frequent and at the same time generic as they are commonly ordered to assess overall health and detect conditions such as anaemia, infection, and leukaemia. Another example is the Urinalysis, which analyzes urine for various substances that can indicate different conditions, such as such as urinary tract infections, kidney disease, and diabetes. Infrequent tests are more specific and targeted, such as the Angiotensin Converting Enzyme (ACE) test, which is used to monitor patients with diagnosed sarcoidosis – a rare disease.

We thus define generic tests as those that were ordered in more than 50,000 cases (i.e., 1% of the tests) across all cases occurring between 2016-2022.[19] We find that physicians significantly reduced orders of generic tests, focusing more on targeted tests (Columns 2 and 3 in Table 4).

Cases with and without tests Finally, we investigate if the improvements in decisions arose from cases that required ordering tests.[20] If information speed improves decisions through the mechanism of changing information acquisition choices, then we should find that cases that did not involve acquiring further information through laboratory tests (e.g., a sprained ankle) should not be affected strongly by the introduction of the technology. Indeed, we find evidence consistent with this hypothesis (see Table A.2 and Table A.3).[21]

[19] We find similar results when we cut the data in alternative ways.

[20] To determine if a diagnosis requires a test, we focus on the 2022 period before the screen's introduction and count the tests each principal medical diagnosis required. If a diagnosis needs at least one test, we categorize it as requiring a test.

[21] Table A.2 shows that the length of stay indeed decreases for cases in which tests were ordered, and not for cases in which they were not. Column 2 shows a slightly negative but statistically insignificant effect of the technology cases that do not involve ordering tests. However, the negative effect is precisely estimated and larger in magnitude when we focus on cases for which physicians order tests (column 3). We further explore the robustness of this result by using variation *within the treated ward*. Table A.3 shows a difference-in-difference design depending on whether the patient had a diagnosis in which a laboratory test needed to be ordered. We find that the length of stay decreases by about 20%, the total cost by 17%, the probability of hospitalization by 4%, and the number of laboratory tests by 20% for patients with a diagnosis that

These results suggest that increased information speed improved physicians' information acquisition choices, reducing the number of tests ordered and shifting them toward more specialized tests.

7.2 The learning mechanism

We now explore the second mechanism: whether obtaining more timely information enabled improved learning from the data required to make the decision (Hypothesis 3(b)). To do this, we explore whether treatment effects were more likely to arise when the ward was busy – when physicians experienced higher cognitive constraints that may have hindered learning.

Table 5 shows the results, cutting the sample by how busy the ward was. For each hour-ward combination, we construct the ratio of patients per physician and label the ward as busy if the ratio is larger than 2, which also represents the 75th percentile of the distribution of patients per physician. Our interpretation of a busy ward is that physicians had more pressure to switch from one patient to another patient. When physicians need to switch across patients, it is likely more difficult to cognitively hold all details of each patient. This means that increasing information speed might enable them to learn better from the information by receiving it at a more optimal time.

—— *Insert Table 5 Here* ——

This table shows that the introduction of the technology indeed had a larger effect during busy hours. For all of our outcome variables, the magnitude of the treatment estimate during busy hours is nearly always more than double the estimate during non-busy hours. This suggests that receiving information in real-time enabled them to make both faster and

require tests *vis a vis* other patients with a diagnosis that do not require laboratory tests.

better decisions, possibly by enabling them to learn better from the information itself.

Common and uncommon diagnoses We also examine how the impact of the technology differed depending on how common the patient's case was – which determines the amount of cognitive effort needed to make inferences and learn from the information acquired. Following Hypothesis 3(b), if learning from information is a key driver, we would expect that the effects should stem mainly from uncommon cases, which require physicians to think carefully through potential hypotheses and diagnoses, compared to more common cases where the diagnoses and necessary tests should be more routine and straightforward.

To investigate, we take the distribution of the universe of diagnoses of patients admitted to the hospital during the period 2016-2022. We label a diagnosis as uncommon if it belongs to the lowest 20th percentile of the distribution, and also examine robustness when cutting at the median. This distribution is heavily concentrated as a few diagnoses represent a large percentage of the population. Table A.4 shows that the effects of the technology on the length of stay mainly occur in uncommon diagnoses when physicians must think through their information acquisition choices, providing additional support for Hypothesis 3.

Mediation analysis To quantify the weight of each mechanism, we conduct a mediation analysis following Heckman and Pinto (2015), focusing on how the information acquisition mechanism mediates the relationship between changes in information speed and length of stay. We report all details in Section A.1. Our findings show that the mediator ratio is 48%, indicating that about half of the treatment effect stems from physicians ordering fewer tests (i.e., their information acquisition choices). This suggests that the remaining 52% of the effect may potentially be attributed to the mechanism of improved learning from the information acquired.

7.3 Alternative mechanisms

In this section, we explore the plausibility of two alternative mechanisms that can have important implications for the interpretation of our results. First, physicians may change their behavior because of peer pressure, rather than increased information speed from the technology adoption. Second, faster decisions (i.e., the decrease in the length of stay) may be driven by the laboratory-processing division analyzing the results of the tests ordered by the private ward more quickly.

Peer effects A potential alternative mechanism is that since the technology leads to other physicians also being notified of test results' statuses, it might increase the motivation of physicians via peer effects. We explore this mechanism by examining treatment effects when multiple physicians are working together, relative to when physicians are working alone – as peer effects should only be triggered when another physician is present in the room.

Table A.5 shows that most of the treatment effects manifest when there is only one physician in the room, suggesting that peer effects are unlikely to be a primary mechanism.

Reaction of the laboratory test unit We investigate whether the finding on faster decisions could be attributed to expedited laboratory test processing for patients in the treated private ward. Our partner organization maintains that this was not a contributing factor. To verify this assertion, we conduct triple-difference estimations using the duration of test processing as the dependent variable. The results, presented in Table A.6, indicate that the laboratory did not accelerate the processing of tests ordered for the private ward following the implementation of the technology *vis a vis* the processing of tests ordered for the non-private ward. This suggests that the observed effect on our measure of decision speed, length of stay, is unlikely to be driven by changes in laboratory test processing times.

8 Discussion and conclusion

In this paper, we explore the impact of information speed on organizational decisions. We find that beyond speeding up a decision, increasing the speed of information substantially improves indicators of organizational performance – improving the throughput, cost efficiency, and quality of care in the ED of a leading hospital.

We find that these improvements stem from two key channels. First, the speed of information enables more effective information acquisition choices: physicians order fewer and more targeted tests. Second, information speed affects how decision-makers learn from the information they acquire, enabling them to make better inferences by receiving information at the time of decision – particularly for uncommon cases where they must think carefully through the information and the potential diagnosis.

One notable aspect of our intervention is that decision-makers may not perceive benefits even when they accrue to the organization. Interviews with physicians revealed that they did not believe the technology improved outcomes. By the time positive effects were analyzed and identified, there was opposition to the technology, which ultimately led to its discontinuation. This is consistent with evidence from many organizations, including those in healthcare, where decision-makers underestimate the benefits of a new technology and resist its adoption (Kassirer, 2000; Benson, 2002; Lapointe and Rivard, 2006; Lin et al., 2012; Boeldt et al., 2015; Gawande, 2018). This suggests that the impacts of technological changes need to be measured and communicated quickly to gain organizational buy-in and enable informed investment decisions.

Of course, our work is not without limitations. First, we are not able to observe all dimensions of physicians' actions, such as the time spent with each patient and their interaction with other physicians. Second, although our partner organization is representative of a large range of EDs in both developed and developing economies, our study focuses on physicians in a single organization, which may limit the generalizability of our findings. We hope future work can explore the extent to which our findings might extend to other contexts, as well as identify their key boundary conditions.

More broadly, these findings suggest that we need to think more deeply about how organizations acquire and learn from information in the digital age. If a marginal improvement in information speed can result in substantial speed-based advantages and enable key decision-makers to improve their choices, this suggests that how organizations build in mechanisms to learn from data may increasingly become a key source of competitive advantage.

References

Adner, R. and Levinthal, D. A. (2004). What is not a real option: Considering boundaries for the application of real options to business strategy. *Academy of Management Review*, 29(1):74–85.

Adner, R., Puranam, P., and Zhu, F. (2019). What is different about digital strategy? from quantitative to qualitative change. *Strategy Science*, 4(4):253–261.

Agarwal, R., Bacco, F., Camuffo, A., Coali, A., Gambardella, A., Msangi, H., Sonka, S. T., Temu, A., Waized, B., and Wormald, A. (2023). Does a theory-of-value add value? evidence from a randomized control trial with tanzanian entrepreneurs. *Working Paper*.

Agrawal, A., Camuffo, A., Gambardella, A., Gans, J., Scott, E., and Stern, S. (2024). Bayesian entrepreneurship. *White Paper*.

Agrawal, A., Gans, J. S., and Goldfarb, A. (2019). Artificial intelligence: the ambiguous labor market impact of automating prediction. *Journal of Economic Perspectives*, 33(2):31–50.

Barends, E. and Rousseau, D. M. (2018). *Evidence-based management: How to use evidence to make better organizational decisions*. Kogan Page Publishers.

Baum, R. and Wally, S. (2003). Strategic decision speed and firm performance. *Strategic Management Journal*, 24(11):1107–1129.

Benson, T. (2002). Why general practitioners use computers and hospital doctors do not—part 1: incentives. *Bmj*, 325(7372):1086–1089.

Berry, D. A. (2004). Bayesian statistics and the efficiency and ethics of clinical trials.

Blank, S. (2013). Why the lean startup changes everything. *Harvard Business Review*.

Bloom, N., Garicano, L., Sadun, R., and Van Reenen, J. (2014). The Distinct Effects of Information Technology and Communication Technology on Firm Organization. *Management Science*, 60(12):2859–2885.

Boeldt, D. L., Wineinger, N. E., Waalen, J., Gollamudi, S., Grossberg, A., Steinhubl, S. R., McCollister-Slipp, A., Rogers, M. A., Silvers, C., and Topol, E. J. (2015). How consumers and physicians view new medical technology: comparative survey. *Journal of medical Internet research*, 17(9):e215.

Bojinov, I. and Gupta, S. (2022). Online experimentation: Benefits, operational and methodological challenges, and scaling guide.

Brynjolfsson, E. and McElheran, K. (2016). The rapid adoption of data-driven decision-making. *American Economic Review*, 106(5):133–39.

Brynjolfsson, E. and McElheran, K. (2019). Data in action: data-driven decision making and predictive analytics in us manufacturing. *Rotman School of Management Working Paper*, (3422397).

Callaway, B. and Sant'Anna, P. H. (2021). Difference-in-Differences with Multiple Time Periods. *Journal of Econometrics*, 225(2):200–230.

Camuffo, A., Cordova, A., Gambardella, A., and Spina, C. (2020). A scientific approach to entrepreneurial decision making: Evidence from a randomized control trial. *Management Science*, 66(2):564–586.

Camuffo, A., Gambardella, A., and Pignataro, A. (2023). Theory-driven strategic management decisions. Technical report, CEPR Discussion Papers.

Chan, D. C. (2016). Teamwork and Moral Hazard: Evidence from the Emergency Department. *Journal of Political Economy*, 124(3):734–770.

Chan, D. C. (2018). The Efficiency of Slacking off: Evidence From the Emergency Department. *Econometrica*, 86(3):997–1030.

Chan, D. C. and Chen, Y. (2022). The Productivity of Professions: Evidence from the Emergency Department. Working Paper 30608, National Bureau of Economic Research.

de Chaisemartin, C. and D'Haultfeuille, X. (2017). Fuzzy Differences-in-Differences. *The Review of Economic Studies*, 85(2):999–1028.

Eisenhardt, K. M. (1989). Making fast strategic decisions in high-velocity environments. *Academy of Management Journal*, 32(3):543–576.

Eisenmann, T. R., Ries, E., and Dillard, S. (2012). *Hypothesis-driven entrepreneurship: The lean startup*. SSRN.

Forbes, D. P. (2005). Managerial determinants of decision speed in new ventures. *Strategic Management Journal*, 26(4):355–366.

Galdon-Sanchez, J. E., Gil, R., and Uriz Uharte, G. (2024). The value of information in competitive markets: The impact of big data on small and medium enterprises. *Forthcoming, Journal of Political Economy*.

Gans, J. S., Stern, S., and Wu, J. (2019). Foundations of entrepreneurial strategy. *Strategic Management Journal*, 40(5):736–756.

Garduno, C. (2022). How big data is helping advertisers solve problems. *Forbes*.

Garud, R., Jain, S., and Phelps, C. (1998). A tale of two browsers. *New York University Teaching Case*.

Gawande, A. (2018). Why doctors hate their computers. *The New Yorker*, 12.

Goldfarb, A. and Tucker, C. (2019). Digital economics. *Journal of Economic Literature*, 57(1):3–43.

Goodman-Bacon, A. (2021). Difference-in-Differences with Variation in Treatment Timing. *Journal of Econometrics*, 225(2):254–277.

Guagenti, P. (2019). Why real-time data matters in financial services. *International Banker*.

Hawk, A., Pacheco-De-Almeida, G., and Yeung, B. (2013). Fast-mover advantages: Speed capabilities and entry into the emerging submarket of atlantic basin lng. *Strategic Management Journal*, 34(13):1531–1550.

Hawser, A. (2022). Banks' eyes in the sky. *The Banker*.

Heckman, J. J. and Pinto, R. (2015). Econometric Mediation Analyses: Identifying the Sources of Treatment Effects from Experimentally Estimated Production Technologies with Unmeasured and Mismeasured Inputs. *Econometric Reviews*, 34(1-2):6–31.

Helfat, C. E., Finkelstein, S., Mitchell, W., Peteraf, M., Singh, H., Teece, D., and Winter, S. G. (2009). *Dynamic capabilities: Understanding strategic change in organizations*. John Wiley & Sons.

Kassirer, J. P. (2000). Patients, physicians, and the internet: Coming generations of doctors are ready to embrace new technology, but few incentives now exist to encourage their older peers to do likewise. *Health Affairs*, 19(6):115–123.

Kerr, W. R., Nanda, R., and Rhodes-Kropf, M. (2014). Entrepreneurship as experimentation. *Journal of Economic Perspectives*, 28(3):25–48.

Kim, H. (2023). The value of competitor information: Evidence from a field experiment. Technical report.

Kim, H., Glaeser, E. L., Hillis, A., Kominers, S. D., and Luca, M. (2024). Decision authority and the returns to algorithms. *Strategic Management Journal*, 45(4):619–648.

Koning, R., Hasan, S., and Chatterji, A. (2022). Experimentation and start-up performance: Evidence from a/b testing. *Management Science*, 68(9):6434–6453.

Lachman, R., Lachman, J. L., and Butterfield, E. C. (2015). *Cognitive psychology and information processing: An introduction*. Psychology Press.

Langley, A. (1995). Between'paralysis by analysis' and'extinction by instinct'. *MIT Sloan Management Review*, 36(3):63.

Lapointe, L. and Rivard, S. (2006). Getting physicians to accept new information technology: insights from case studies. *Cmaj*, 174(11):1573–1578.

Leatherbee, M. and Katila, R. (2020). The lean startup method: Early-stage teams and hypothesis-based probing of business ideas. *Strategic Entrepreneurship Journal*, 14(4):570–593.

Levinthal, D. A. (2017). Mendel in the c-suite: Design and the evolution of strategies. *Strategy Science*, 2(4):282–287.

Lin, C., Lin, I.-C., and Roan, J. (2012). Barriers to physicians' adoption of healthcare information technology: an empirical study on multiple hospitals. *Journal of medical systems*, 36:1965–1977.

Makadok, R. (1998). Can first-mover and early-mover advantages be sustained in an industry with low barriers to entry/imitation? *Strategic Management Journal*, 19(7):683–696.

Mani, A., Mullainathan, S., Shafir, E., and Zhao, J. (2013). Poverty impedes cognitive function. *science*, 341(6149):976–980.

Mao, J. and Bojinov, I. (2021). Quantifying the value of iterative experimentation. *arXiv preprint arXiv:2111.02334*.

McAfee, A., Brynjolfsson, E., Davenport, T. H., Patil, D., and Barton, D. (2012). Big data: the management revolution. *Harvard Business Review*, 90(10):60–68.

Miller, G. A. (1956). The magical number seven, plus or minus two: Some limits on our capacity for processing information. *Psychological Review*, 63(2):81.

Mosakowski, E. (1997). Strategy making under causal ambiguity: Conceptual issues and empirical evidence. *Organization Science*, 8(4):414–442.

Nagaraj, A. (2022). The private impact of public data: Landsat satellite maps increased gold discoveries and encouraged entry. *Management Science*, 68(1):564–582.

Newsweek (2024). The World's Best Hospitals 2024.

Osipovich, A. (2020). High-frequency traders push closer to light speed with cutting-edge cables. *Wall Street Journal*.

Pacheco-de Almeida, G., Hawk, A., and Yeung, B. (2015). The right speed and its value. *Strategic Management Journal*, 36(2):159–176.

Perlow, L. A., Okhuysen, G. A., and Repenning, N. P. (2002). The speed trap: Exploring the relationship between decision making and temporal context. *Academy of Management Journal*, 45(5):931–955.

Pfeffer, J. and Sutton, R. I. (2000). *The knowing-doing gap: How smart companies turn knowledge into action*. Harvard Business Press.

Pfeffer, J. and Sutton, R. I. (2006). Evidence-based management. *Harvard Business Review*, 84(1):62.

Rambachan, A. and Roth, J. (2023). A more credible approach to parallel trends. *Review of Economic Studies*, 90(5):2555–2591.

Ries, E. (2011). *The lean startup: How today's entrepreneurs use continuous innovation to create radically successful businesses*. Crown Currency.

Shanmugam, P. V. (2020). Decision-making under cognitive constraints: Evidence from the emergency department. *Sementic Scholar*, pages 1–88.

Simon, H. A. (1991). Bounded rationality and organizational learning. *Organization Science*, 2(1):125–134.

Stalk, G. (1988). Time–the next source of competitive advantage. *Harvard Business Review*.

Stalk Jr, G. and Hout, T. M. (1990). Competing against time. *Research-Technology Management*, 33(2):19–24.

Teece, D. J., Pisano, G., and Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal*, 18(7):509–533.

Figures and Tables

TABLE 1: SUMMARY STATISTICS

Obs. = 64,152; Patients = 43,607; Doctors = 387.

	Mean	SD	p10	p25	p50	p75	p90
Outcome Variables:							
Length of Stay (Days)	.55	.66	.04	.1	.22	.79	2
Number of Tests	6.29	10.16	0	0	3	8	16
Total Cost	13.62	1.85	11.55	12.44	13.15	14.77	16.43
Hospitalization	.25	.43	0	0	0	0	1
30-Day Return	.13	.34	0	0	0	0	1
Independent Variables:							
Private Ward	.59	.49	0	0	1	1	1
Post June	.51	.5	0	0	1	1	1
Selected Control Variables:							
Male Patient	.42	.49	0	0	0	1	1
Patient Age	47.47	19.29	23	31	45	62	75
Triage 1	.05	.22	0	0	0	0	0
Triage 2	.25	.44	0	0	0	1	1
Triage 3	.37	.48	0	0	0	1	1
Triage 4	.3	.46	0	0	0	1	1

Note: This table displays summary statistics for the main variables in the empirical analysis. Length of stay is the time between triage and the departure of the patient from the ED (i.e. discharge or hospital admission). Number of tests is the number of laboratory tests ordered during the patient stay in the ED. Total cost (defined as the log of the amount in Colombian Pesos (COP) charged by the hospital to the patient for each episode). The hospital admission dummy takes value one if the patient was admitted to the hospital instead of discharged home. The 30-day return dummy takes value one if the patient returns to the ED within 30 days. The table also includes a dummy for the private ward and a dummy for episodes after June of each year. Control variables include a dummy when the patient is male, the patient's age, and a dummy for each one of the four first triages. The sample includes the universe of medical episodes between March and October for two years: 2019 and 2022.

TABLE 2: THE IMPACT OF INFORMATION SPEED ON TIME TO DECISION

Dependent Variable = Log Length of Stay

	(1)	(2)	(3)	(4)	(5)	(6)
Post June X Private Ward X Year 2022	-.254	-.383	-.352	-.163	-.124	-.133
	(.063)	(.089)	(.085)	(.049)	(.059)	(.051)
Post June X Private Ward	Yes	Yes	Yes	Yes	Yes	Yes
Patient Controls X Year 2022	No	No	No	Yes	Yes	Yes
Doctor Fixed Effects X Year 2022	No	No	Yes	Yes	Yes	Yes
Insurance Status Fixed Effects X Year 2022	No	Yes	Yes	Yes	Yes	Yes
Date X Hour Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Post June X Year 2022	Yes	No	No	No	No	No
Private Ward X Year 2022	Yes	No	No	No	No	No
Observations	63,025	61,750	61,612	62,618	40,830	61,600

Note: This Table displays estimates of regressions of a case's length of stay in the ED on the period during which the technology was introduced (i.e. after June), interacted with the ward in which it was introduced (i.e. private ward) and with the year 2022 dummy. The unit of observation is a case i arriving at the ED. The estimating equation in Column 4 is:

$$y_i = \beta(Private_{w(i)} \times Post_{t(i)} \times 2022_{t(i)}) + \alpha_{d(i)} + \theta_{w(i)} + \pi_{t(i)} + \gamma'(\mathbf{X_i} \times 2022_{t(i)}) + \epsilon_i$$

where w indexes the ward to which the patient is assigned, t indexes the exact hour (i.e. date/hour of day combination) in which the patient arrived and d indexes the physician to which the patient was assigned. The main independent variable of interest is the interaction between being assigned to the private ward, arriving in the months between July and October, and arriving in 2022. The model controls for insurance status (which subsumes the assigned ward), physician and hour-fixed effects, as well as patient controls (age, gender, dummies for the main diagnosis, as well as dummies for extreme vital signs markers upon admission). All the patient controls are interacted with the year 2022 dummy. In Column 1 we display the most streamlined triple-differences model, which only includes a post dummy and a private dummy as controls, interacted with each other and with the year 2022 dummy, this regression includes all triages in its estimation and length of stay is not winsorized. In Column 2 we include the insurance status and the hour fixed effects (which subsume the year 2022 and private ward dummies), this regression includes all triages in its estimation, and the length of stay is not winsorized. In Column 3 we add the physician fixed effects, this regression includes all triages in its estimation, and length of stay is not winsorized. In Column 4 we add the patient controls and the top and bottom 1% of the length of stay distribution is winsorized, this regression includes all triage in its estimation. In Column 5 we add the patient controls and the sample includes only triage levels 1–3 and the length of stay is not winsorized. Column 6 is the baseline model for the full sample, this regression includes all triages in its estimation, and length of stay is not winsorized. Standard errors are clustered at the physician level.

TABLE 3: THE IMPACT OF INFORMATION SPEED ON OTHER ORGANIZATIONAL OUTCOMES

PANEL A: EFFECTS ON COSTS AND QUALITY OF CARE

Dependent Variable =	(1) Total Cost	(2) Hospitalization	(3) 30–Day Return
Post June X Private Ward X Year 2022	-.255	-.071	.01
	(.059)	(.014)	(.013)
Patient Controls X Year 2022	Yes	Yes	Yes
Doctor Fixed Effects X Year 2022	Yes	Yes	Yes
Insurance Status Fixed Effects X Year 2022	Yes	Yes	Yes
Date X Hour Fixed Effects	Yes	Yes	Yes
Observations	62,546	62,650	62,650

PANEL B: EFFECTS ON PATIENT SATISFACTION

	(1) Attitude	(2) Compliance	(3) Answering Questions	(4) Average
Post June X Private Ward	.201	.156	.18	.171
	(.059)	(.064)	(.058)	(.057)
Patient Controls	Yes	Yes	Yes	Yes
Doctor Fixed Effects	Yes	Yes	Yes	Yes
Insurance Status Fixed Effects	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes
Mean Dep. Var.	3.68	3.6	3.65	3.62
SD Dep. Var.	.54	.59	.58	.54
Observations	1,445	1,233	1,443	1,232

Note: Panel A table displays estimates of regressions of a case's different medical outcomes in the ED on the period during which the technology was introduced (i.e. after June), interacted with the ward in which it was introduced (i.e. private ward) and with the year 2022 dummy. The estimating equation is:

$$y_i = \beta(Private_{w(i)} \times Post_{t(i)} \times 2022_{t(i)}) + \alpha_{d(i)} + \theta_{w(i)} + \pi_{t(i)} + \gamma'(\mathbf{X_i} \times 2022_{t(i)}) + \epsilon_i$$

The model controls for insurance status (which subsumes the assigned ward), physician and hour-fixed effects, as well as patient controls (age, gender, dummies for the main diagnosis, as well as dummies for extreme vital signs markers upon admission). In column 1, the dependent variable is the total cost (defined as the log of the amount in Colombian Pesos (COP) charged by the hospital to the patient for each episode). In Column 2, the dependent variable is a dummy if the patient is hospitalized. In Column 3, the dependent variable is a dummy that takes the value of 1 if the patient returns to the ED within a 30-days period. All the controls are interacted with the year 2022 dummy. Panel B table displays estimates of regressions of patients' evaluations in the ED on the period during which the technology was introduced, and interacted with the ward in which it was introduced. The estimating equation is:

$$y_i = \beta(Private_{w(i)} \times Post_{t(i)}) + \alpha_{d(i)} + \theta_{w(i)} + \pi_{t(i)} + \gamma'\mathbf{X_i} + \epsilon_i$$

The main independent variable of interest is the interaction between being assigned to the private ward and arriving in the month of July or after. The model controls for insurance status (which subsumes the assigned ward), physician and month-fixed effects, as well as patient controls (age, gender, dummies for the main diagnosis, as well as dummies for extreme vital signs markers upon admission). For both panels where w indexes the ward to which the patient is assigned, t indexes the month in which the patient arrived, and d indexes the physician to which the patient was assigned. The unit of observation is a case i arriving to the ED. Standard errors are clustered at the physician level.

TABLE 4: EVIDENCE ON THE INFORMATION ACQUISITION MECHANISM

	Log. Number of Tests	Type of Tests		Percentiles			
		Targeted	Generic	0–25	25–50	50–75	75–100
Post June X Private Ward X Year 2022	-.102	-.042	-.102	-.021	-.117	-.001	-2.335
	(.037)	(.032)	(.034)	(.034)	(.123)	(.326)	(.53)
Post June X Private Ward	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Patient Controls X Year 2022	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Doctor Fixed Effects X Year 2022	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Insurance Status Fixed Effects X Year 2022	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date X Hour Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	62,650	62,650	62,650	30,163	5,886	1,483	1,315

Note: This Table displays estimates of regressions of the log. of the number of tests on the period during which the technology was introduced (i.e. after June), interacted with the ward in which it was introduced (i.e. private ward) and with the year 2022 dummy. To determine whether the test is generic, we defined it as 1 (generic) if the test category appears in 50.000 (the median value) or more episodes and 0 otherwise. 50.000 episodes represent the 99% percentile of the distribution of laboratory tests. The last four columns show the effect of the interaction term on the log number of tests cutting the sample into 4 quartiles of the length of stay. For instance, the column 0-25 shows the effect of the change of the speed on information on the number of tests for the first quarter of the episode. The estimating equation is:

$$y_i = \beta(Private_{w(i)} \times Post_{t(i)} \times 2022_{t(i)}) + \alpha_{d(i)} + \theta_{w(i)} + \pi_{t(i)} + \gamma'(\mathbf{X_i} \times 2022_{t(i)}) + \epsilon_i$$

where w indexes the ward to which the patient is assigned, t indexes the exact hour (i.e. date/hour of day combination) in which the patient arrived and d indexes the physician to which the patient was assigned. The main independent variable of interest is the interaction between being assigned to the private ward, arriving in the months between July and October, and arriving in 2022. The model controls for insurance status (which subsumes the assigned ward), physician and hour fixed effects, as well as patient controls (age, gender, dummies for the main diagnosis, as well as dummies for extreme vital signs markers upon admission) interacted with the year 2022 dummy. Standard errors are clustered at the physician level.

TABLE 5: EVIDENCE CONSISTENT WITH THE LEARNING MECHANISM

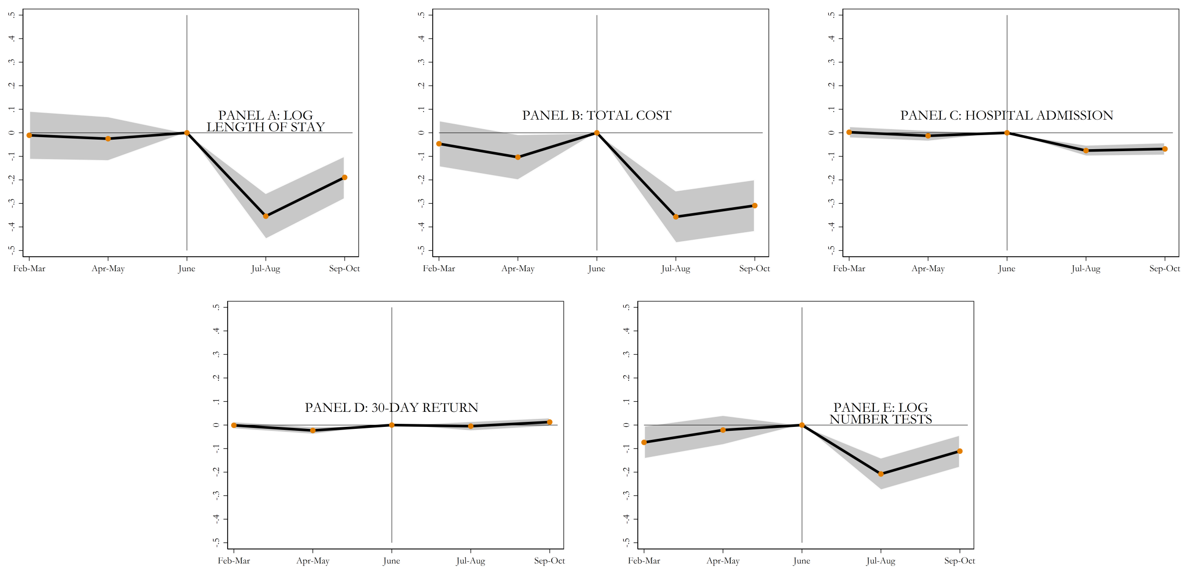
	Log. Length of Stay		**Total Cost**		**Hospitalization**		**30–Day Return**		**Log. Number of Tests**	
	Busy	**Non-Busy**	**Busy**	**Non-Busy**	**Busy**	**Non-Busy**	**Busy**	**Non-Busy**	**Busy**	**Non-Busy**
Post June X Private Ward X Year 2022	-.533	-.132	-.438	-.328	-.144	-.057	.054	.001	-.497	-.108
	(.211)	(.062)	(.242)	(.077)	(.051)	(.017)	(.063)	(.015)	(.154)	(.043)
Patient Controls X Year 2022	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Doctor Fixed Effects X Year 2022	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Insurance Status Fixed Effects X Year 2022	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date X Hour Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,889	43,064	18,151	43,773	18,190	43,839	18,190	43,839	18,190	43,839

Note: This Table displays estimates of regressions of a case's log length of stay, total cost, Hospitalization, 30-day return, and log of the number of tests in the ED on the period during which the informational screen was introduced (i.e. after June), interacted with the ward in which it was introduced (i.e. private ward) and with the year 2022 dummy. This table shows results for different samples according to busy or non-busy hours. The percentile 75 for the patient-physician ratio is near 2 patients per physician. So, busy hours are defined as hours where there are more than 2 patients per physician. The unit of observation is a case i arriving at the ED. The estimating equation is:

$$y_i = \beta(Private_{w(i)} \times Post_{t(i)} \times 2022_{t(i)}) + \alpha_{d(i)} + \theta_{w(i)} + \pi_{t(i)} + \gamma'(\mathbf{X_i} \times 2022_{t(i)}) + \epsilon_i$$

where w indexes the ward to which the patient is assigned, t indexes the exact hour (i.e. date/hour of day combination) in which the patient arrived and d indexes the physician to which the patient was assigned. The main independent variable of interest is the interaction between being assigned to the private ward, arriving in the months between July and October, and arriving in 2022. The model controls for insurance status (which subsumes the assigned ward), physician and hour fixed effects, as well as patient controls (age, gender, dummies for the main diagnosis, as well as dummies for extreme vital signs markers upon admission) interacted with the year 2022 dummy. In Columns 1-2, the dependent variable is the length of stay. In Columns 3-4, the dependent variable is the total cost (defined as the log of the amount in Colombian Pesos (COP) charged by the hospital to the patient for each episode). In Columns 5-6, the dependent variable is a dummy if the patient is hospitalized. In Columns 7-8, the dependent variable is a dummy that takes the value of 1 if the patient returns to the ED within a 30-days period. In Columns 9-10, the dependent variable is the number of tests. Within a pair of columns, the first column of each dependent variable shows the busy sample while the second column shows the non-busy sample. Standard errors are clustered at the physician level.

FIGURE 1: LEADS AND LAGS EVIDENCE (TRIPLE-DIFF)



This Figure displays dynamic estimates of regressions of a case's length of stay in the ED on the period during which the technology was introduced and interacted with the ward in which it was introduced (i.e. prepaid ward) and the year 2022. The unit of observation is a case i arriving at the ED. This figure displays the coefficients β_j from estimating:

$$y_i = \sum_{t=2-3,4-5}^{7-8,9-10} \beta_j \big(Private_{w(i)} \times Monthj_{t(i)} \times 2022_{t(i)} \big) + \alpha_{d(i)} + \theta_{w(i)} + \pi_{t(i)} + \gamma' \big(\mathbf{X_i} \times 2022_{t(i)} \big) + \epsilon_i$$

where w indexes the ward to which the patient is assigned, t indexes the exact hour (i.e. date/hour of day combination) in which the patient arrived, and d indexes the physician to which the patient was assigned. The model controls for insurance status (which subsumes the assigned ward), physician and hour-fixed effects, as well as patient controls (age, gender, and health markers upon admission) interacted with the year dummy 2022. Standard errors are clustered at the physician level. To show longer dynamics we increase our sample from March to October (as the rest of the paper), to February to October.

Online Appendix

A.1 Mediation analysis

While identifying the quantitative importance of different mechanisms is a notoriously difficult exercise, in this subsection we examine whether any share in the decrease in the length of stay may be independent from the effects on the number of tests. Firstly, we estimate equation (2) while controlling for the number of tests ordered. We display the results in Column 4 Table A.1. We find there that the baseline triple-differences coefficient decreases in magnitude, and becomes not statistically significant. That is, the decrease in the length of stay becomes much smaller if one holds the number of tests ordered constant. We interpret this result as additional supportive evidence on the information acquisition mechanism – that increasing information speed had an effect in organizational outcomes through the laboratory tests that physicians chose to order.

While enlightening, the evidence in Column 4 Table A.1 can at best only be regarded as suggestive, given that the regressions are controlling for explicitly endogenous variables. For a more systematic analysis, we follow Heckman and Pinto (2015) in quantifying the relative importance of our mediating variable in the estimated decrease in length of stay. Heckman and Pinto (2015) consider an initial model $y_i = \beta_1 \cdot T_i + \beta_2 X_i + \epsilon_i$ where T_i is the introduction of the technology and X_i is a set of controls. The method decomposes the effect of the treatment into two parts:

$$\frac{dy}{dT} = \frac{\partial y}{\partial M} \frac{\partial M}{\partial T} + R \tag{A.1}$$

where M is the mediator –*Number of Tests*–. From (A.1) it is possible to isolate R given information on all other three elements. To do this, we substitute $\frac{dy}{dT}$ by the $\hat{\beta}$ from (2) where length of stay is the dependent variable. Secondly, we estimate $\hat{\beta}_{inter} = \frac{\partial M}{\partial T}$ from again regressing (2) but now having the mediator variable as the dependent variable. Lastly, we add the mediator M as an additional independent variable in (2) and obtain its estimated coefficient $\hat{\beta}_{med}$, which we take as an approximation to $\frac{\partial y}{\partial M}$. We can then define the ratio of mediator j as:

$$\frac{\hat{\beta}_{med(j)} \times \hat{\beta}_{inter(j)}}{\hat{\beta}}$$

We find that the mediator ratio is 48%, suggesting that around half of the treatment effect is due to physicians choosing to acquire different information (in this case, by ordering fewer tests). This implies that around 52% of the effect is independent of the mediating variable – which may be driven by other mechanisms such as the type of tests ordered, as well as the ability to learn better from the information acquired.

Figures and Tables

TABLE A.1: BASELINE FINDINGS

Dependent Variable = Log Length of Stay	**(1)**	**(2)**	**(3)**	**(4)**
	DiD	**Placebo DiD**	**Baseline DiDiD**	**Baseline DiDiD**
Year =	**2022**	**2019**	**2019&2022**	**2019&2022**
Post June X Private Ward	-.247	-.115	-.115	-.095
	(.043)	(.026)	(.026)	(.019)
Post June X Private Ward X Year 2022			-.133	-.051
			(.051)	(.033)
Log Number of Tests				.777
				(.011)
Patient Controls	Yes	Yes	Yes	Yes
Doctor Fixed Effects	Yes	Yes	Yes	Yes
Insurance Status Fixed Effects	Yes	Yes	Yes	Yes
Date X Hour Fixed Effects	Yes	Yes	Yes	Yes
Interactions with 2022 dummy	No	No	Yes	Yes
Observations	29,108	32,492	61,600	61,600

Note: This Table displays estimates of regressions of a case's length of stay in the ED on the period during which the technology was introduced (i.e. after June), interacted with the ward in which it was introduced (i.e. private ward). The unit of observation is a case i arriving at the ED. The estimating equation in Columns 1 and 2 is:

$$y_i = \beta(Private_{w(i)} \times Post_{t(i)}) + \alpha_{d(i)} + \theta_{in(i)} + \pi_{t(i)} + \gamma'\mathbf{X_i} + \epsilon_i$$

where w indexes the ward to which the patient is assigned, t indexes the exact hour (i.e. date/hour of day combination) in which the patient arrived and d indexes the physician to which the patient was assigned. Column 1 (2) shows the results of running this regression only for 2022 (2019). The main independent variable of interest is the interaction between being assigned to the private ward and arriving in the month of July or after. The model controls for insurance status (which subsumes the assigned ward), physician and hour-fixed effects, as well as patient controls (age, gender, dummies for the main diagnosis, as well as dummies for extreme vital signs markers upon admission). In Column 2 we repeat the Column 1 exercise on the placebo sample of 2019. In Columns 3 and, 4 the sample includes cases from both 2019 and 2022. The main independent variable of interest is the triple interaction between the private ward, the after-June dummy, and the 2022 dummy. The model controls for the interactions between all the controls and the year 2022 dummy. Standard errors are clustered at the physician level.

TABLE A.2: **LENGTH OF STAY WITH AND WITHOUT TESTS**

	(1) All Episodes	(2) Without Tests	(3) With Tests
Post June X Private Ward X Year 2022	-.133	-.072	-.156
	(.051)	(.067)	(.052)
Post June X Private Ward	Yes	Yes	Yes
Patient Controls X Year 2022	Yes	Yes	Yes
Doctor Fixed Effects X Year 2022	Yes	Yes	Yes
Insurance Status Fixed Effects X Year 2022	Yes	Yes	Yes
Date X Hour Fixed Effects	Yes	Yes	Yes
Post June X Year 2022	No	No	No
Private Ward X Year 2022	No	No	No
Observations	61,600	20,892	37,270

Note: This Table displays estimates of regressions of a case's length of stay in the ED on the period during which the informational screen was introduced (i.e. post 18 June), interacted with the ward in which it was introduced (i.e. private ward) and with the year 2022 dummy. The unit of observation is a case i arriving at the ED. The estimating equation is:

$$y_i = \beta(Private_{w(i)} \times Post_{t(i)} \times 2022_{t(i)}) + \alpha_{d(i)} + \theta_{w(i)} + \pi_{t(i)} + \gamma'(\mathbf{X_i} \times 2022_{t(i)}) + \epsilon_i$$

where w indexes the ward to which the patient is assigned, t indexes the exact hour (i.e. date/hour of day combination) in which the patient arrived and d indexes the physician to which the patient was assigned. The main independent variable of interest is the interaction between being assigned to the private ward, arriving in the months between July and October, and arriving in 2022. The model controls for insurance status (which subsumes the assigned ward), physician and hour fixed effects, as well as patient controls (age, gender, dummies for the main diagnosis, as well as dummies for extreme vital signs markers upon admission) interacted with the year 2022 dummy. Column 1 includes all episodes. Column 2 only includes episodes in which no tests were requested, while Column 3 only includes episodes in which there was at least one requested test. Standard errors are clustered at the physician level.

TABLE A.3: THE IMPACT OF DIAGNOSTIC WITH TESTS ON MAIN OUTCOMES

Dependent Variable =	(1) Log. Length of Stay	(2) Total Cost	(3) Hospital.	(4) 30–Day Return	(5) Log. Number of Tests
Post June X Diag. with Test	-.203	-.173	-.04	.001	-.197
	(.05)	(.062)	(.017)	(.017)	(.036)
Patient Controls X Year 2022	Yes	Yes	Yes	Yes	Yes
Dr. Fixed Effects X Year 2022	Yes	Yes	Yes	Yes	Yes
Ins. Fixed Effects X Year 2022	Yes	Yes	Yes	Yes	Yes
Date X Hour Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	35,712	36,066	36,100	36,100	36,100

Note: This table displays estimates of regressions of a case's different medical outcomes in the ED on the period during which the technology was introduced (i.e. after June), interacted with a dummy equal to 1 for diagnosis with tests (defined as a diagnosis that received at least one test in the first semester of 2022 (excluding June)) and 0 otherwise. The estimating equation is:

$$y_i = \beta(\times Post_{t(i)} \times DiagTest_i) + \alpha_{d(i)} + \theta_{w(i)} + \pi_{t(i)} + \gamma'(\mathbf{X_i}) + \epsilon_i$$

The model controls for insurance status (which subsumes the assigned ward), physician and hour-fixed effects, as well as patient controls (age, gender, dummies for the main diagnosis, as well as dummies for extreme vital signs markers upon admission). In column 1, the dependent variable is the case's length of stay in the ED. In column 2, the dependent variable is the total cost (defined as the log of the amount in Colombian Pesos (COP) charged by the hospital to the patient for each episode). In Column 3, the dependent variable is a dummy if the patient is hospitalized. In Column 4, the dependent variable is a dummy that takes the value of 1 if the patient returns to the ED within a 30–day period. The last column has the logarithm of the number of tests as dependent variables. Standard errors are clustered at the physician level.

TABLE A.4: LENGTH OF STAY BY DIAGNOSIS CLASSIFICATION

	(1)	(2)	(3)	(4)	(5)
	All Diagnosis	**Common** (20/80 Spilt) **Diagnosis**	**Uncommon** (20/80 Spilt) **Diagnosis**	**Common** (50/50 Spilt) **Diagnosis**	**Uncommon** (50/50 Spilt) **Diagnosis**
Post June X Private Ward X Year 2022	-.133	.019	-.378	-.13	-.427
	(.051)	(.13)	(.079)	(.082)	(.092)
Patient Controls X Year 2022	Yes	Yes	Yes	Yes	Yes
Doctor Fixed Effects X Year 2022	Yes	Yes	Yes	Yes	Yes
Insurance Status Fixed Effects X Year 2022	Yes	Yes	Yes	Yes	Yes
Date X Hour Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	61,600	9,977	47,651	24,385	33,735

Note: This Table displays estimates of regressions of a case's log. length of stay. The estimating equation is:

$$y_i = \beta(Private_{w(i)} \times Post_{t(i)} \times 2022_{t(i)}) + \theta_{w(i)} + \pi_{t(i)} + \gamma'(\mathbf{X_i} \times 2022_{t(i)}) + \epsilon_i$$

where w indexes the ward to which the patient is assigned, t indexes the exact hour (i.e. date/hour of day combination) in which the patient arrived and d indexes the physician to which the patient was assigned. The main dependent variable of interest is the length of stay. The model controls for insurance status (which subsumes the assigned ward), physician and hour fixed effects, as well as patient controls (age, gender, dummies for the main diagnosis, as well as dummies for extreme vital signs markers upon admission) interacted with the year 2022 dummy. Standard errors are clustered at the physician level. Column 1 includes episodes of all the diagnoses. Column 2 includes only the common diagnosis and Column 3 includes the uncommon diagnosis, both based on a 20%–80% distribution cut. Column 4 includes only the common diagnosis and Column 5 includes the uncommon diagnosis, both based on a 50%–50% distribution cut.

TABLE A.5: LIMITED EVIDENCE OF PEER EFFECTS

	Log. Length of Stay		Log. Number of Tests		Total Cost		Hospitalization		30-Day Return	
	Number of Drs.		Number of Drs.		Number of Drs.		Number of Drs.		Number of Drs.	
	1	2+	1	2+	1	2+	1	2+	1	2+
Post June X Private Ward X 2022	-.251	-.068	-3.617	-.294	-.605	-.055	-.174	-.02	.027	-.018
	(.021)	(.056)	(.294)	(1.306)	(.055)	(.131)	(.014)	(.04)	(.018)	(.036)
Patient Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Doctor Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Insurance Status Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date X Hour Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	46,629	12,829	46,629	12,829	46,562	12,796	46,629	12,829	46,629	12,829

Note: This Table displays estimates of regressions of a case's number of physicians working in an episode on patient outcomes on the period during which the informational screen was introduced (i.e. after June), interacted with the ward in which it was introduced (i.e. private ward) and with the year 2022 dummy. To define the number of physicians working in an hour–ward–episode, we count the total number of physicians that are directly treating patients, that are requesting tests for patients, or that close any ED episode. The estimating equation is:

$$y_i = \beta(Private_{w(i)} \times Post_{t(i)} \times 2022_{t(i)}) + \alpha_{d(i)} + \theta_{w(i)} + \pi_{t(i)} + \gamma'(\mathbf{X_i} \times 2022_{t(i)}) + \epsilon_i$$

where w indexes the ward to which the patient is assigned, t indexes the exact hour (i.e. date–hour of day combination) in which the patient arrived and d indexes the physician to which the patient was assigned. The main independent variable of interest is the interaction between being assigned to the private ward, arriving in the months between July and October, and arriving in 2022. The model controls for insurance status (which subsumes the assigned ward), physician and hour fixed effects, as well as patient controls (age, gender, dummies for the main diagnosis, as well as dummies for extreme vital signs markers upon admission) interacted with the year 2022 dummy. Sample changes for each column depending on the number of physicians working on an episode (treatment physician and other physicians who request tests). Standard errors are clustered at the physician level.

TABLE A.6: LENGTH OF TEST PROCESSING

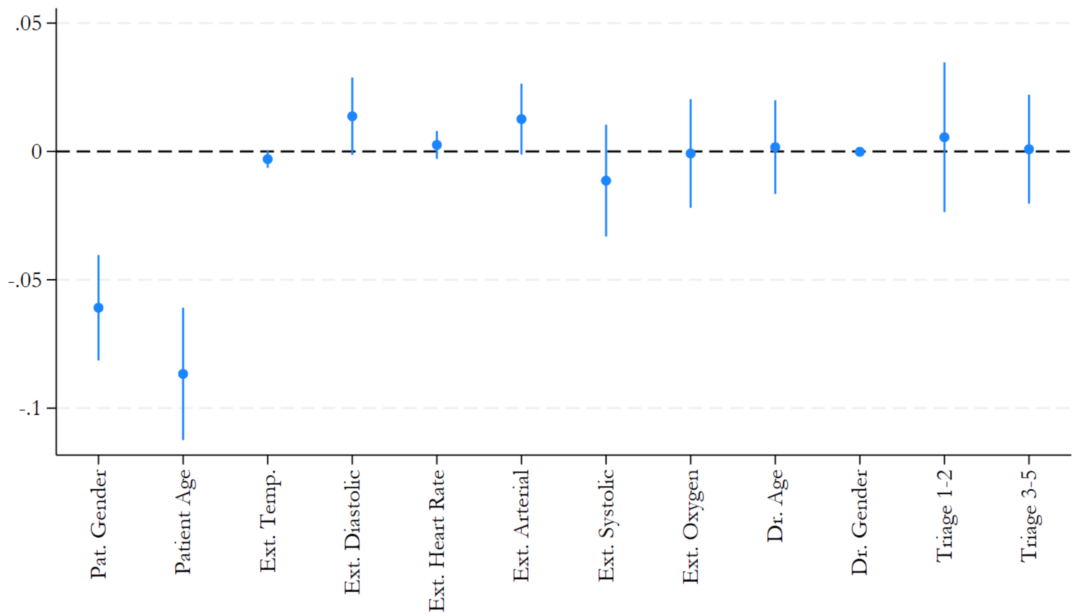
	(1)	(2)	(3)	(4)	(5)
Post June X Private Ward X Year 2022	-.001	.005	.009	.045	-.026
	(.035)	(.034)	(.034)	(.033)	(.031)
Patient Controls X Year 2022	Yes	No	Yes	Yes	Yes
Doctor Fixed Effects	Yes	Yes	No	Yes	Yes
Insurance Status Fixed Effects	Yes	Yes	Yes	No	Yes
Date X Hour Fixed Effects	Yes	Yes	Yes	Yes	No
Observations	37,555	37,555	37,701	37,555	39,507

Note: This Table displays estimates of regressions of a case's the total time that the test took to be delivered in the laboratory department on the period during which the technology was introduced (i.e. after June), interacted with the ward in which it was introduced (i.e. private ward) interacted with the year 2022. The unit of observation is a case i arriving at the ED. The estimating equation is:

$$y_i = \beta(Private_{w(i)} \times Post_{t(i)} \times 2022_{t(i)}) + \alpha_{d(i)} + \theta_{w(i)} + \pi_{t(i)} + \gamma'(\mathbf{X_i} \times 2022_{t(i)}) + \epsilon_i$$

where w indexes the ward to which the patient is assigned, t indexes the exact hour (i.e. date–hour of day combination) in which the patient arrived, and d indexes the physician to which the patient was assigned. The main independent variable of interest is the interaction between being assigned to the private ward, arriving in the months between July and October, and arriving in 2022. The model controls for insurance status (which subsumes the assigned ward), physician and hour–fixed effects, as well as patient controls (age, gender, dummies for the main diagnosis, as well as dummies for extreme vital signs markers upon admission) interacted with the 2022 dummy. Standard errors are clustered at the physician level.

FIGURE A.1: **EXOGENEITY**

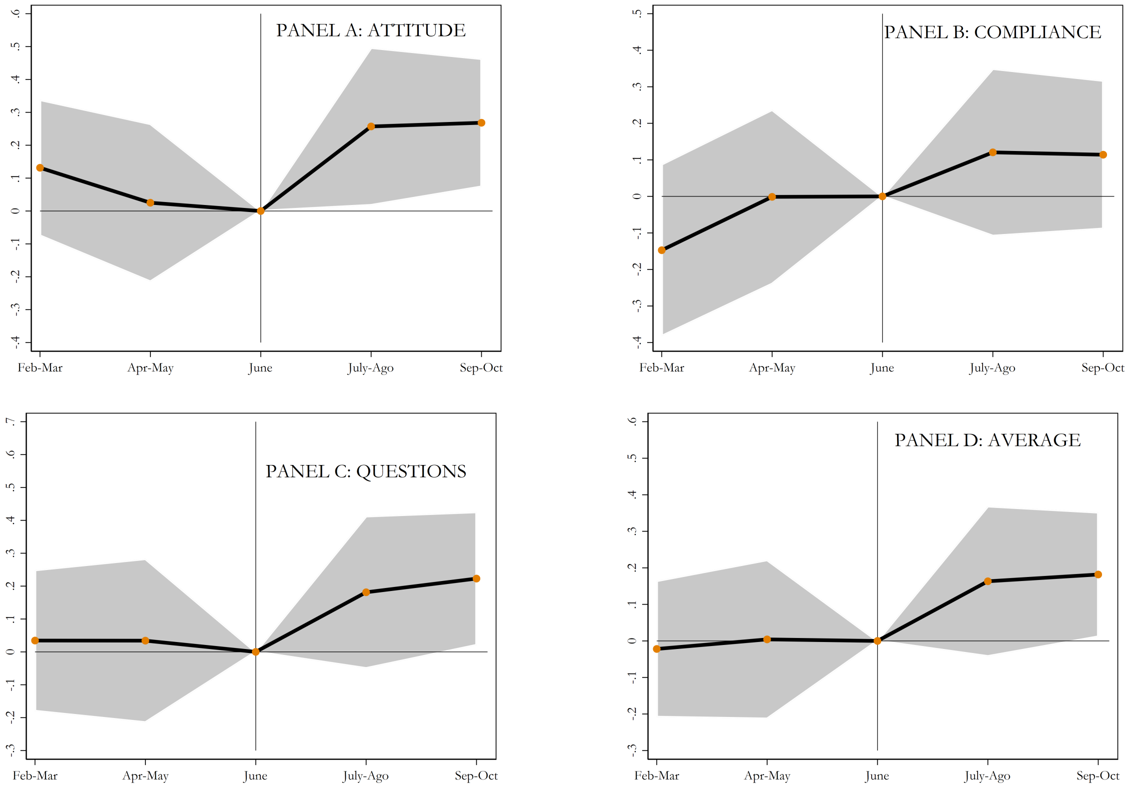


Note: This figure displays coefficients of different regressions for the following dependent variables y_i: Patient Gender (dummy defined as 1 for men and 0 for women), Patient Age dummy defined as 1 for patients whose age is above the median and 0 otherwise, Extreme Vital Signs (diastolic pressure, heart rate, arterial pressure, systolic pressure and oxygen saturation), Dr. Age dummy defined as 1 for physicians whose age is above the median and 0 otherwise, Dr. Gender (dummy defined as 1 for men and 0 for women), low triage dummy defined as 1 for triages 1 and 2 and 0 otherwise. The estimating equation is:

$$y_i = \beta(Private_{w(i)} \times Post_{t(i)} \times 2022_{t(i)}) + \theta_{w(i)} + \pi_{t(i)} + \gamma'(\mathbf{X_i} \times 2022_{t(i)}) + \epsilon_i$$

where w indexes the ward to which the patient is assigned, t indexes the exact hour (i.e. date–hour of day combination) in which the patient arrived and d indexes the physician to which the patient was assigned. The model controls for insurance status (which subsumes the assigned ward), physician and hour fixed effects, as well as patient controls (age, gender, dummies for the main diagnosis, as well as dummies for extreme vital signs markers upon admission) interacted with the year 2022 dummy. When the variable is the dependent variable, it is excluded from the control list. For instance, for the first variable, the dependent variable is patient gender and in this case, is excluded from the list $\mathbf{X_i}$. Standard errors are clustered at the physician level.

FIGURE A.2: LEADS AND LAGS EVIDENCE DOUBLE-DIF

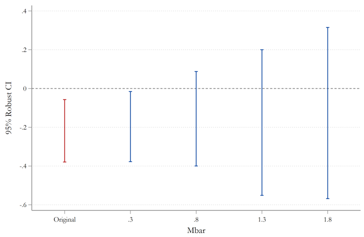


This Figure displays dynamic estimates of regressions of a case's survey evaluation on the period during which the technology was introduced (i.e. after June), interacted with the ward in which it was introduced (i.e. private ward). The unit of observation is a case i arriving at the ED. This figure displays the coefficients β_t from estimating:

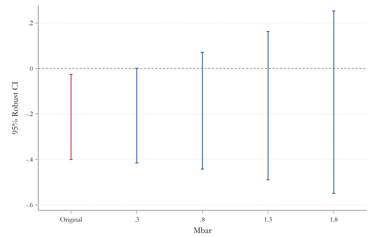
$$y_i = \sum_{t=2-3,4-5}^{7-8,9-10} \beta_t (Prepaid_{w(i)} \times Month_{t(i)}) + \alpha_{d(i)} + \theta_{w(i)} + \pi_{t(i)} + \gamma' \mathbf{X_i} + \epsilon_i$$

where w indexes the ward to which the patient is assigned, t indexes the exact hour (i.e. date/hour of day combination) in which the patient arrived, and d indexes the physician to which the patient was assigned. The main independent variable of interest is the interaction between being assigned to the prepaid ward and arriving after June. The model controls for insurance status (which subsumes the assigned ward), physician and hour-fixed effects, as well as patient controls (age, gender, and health markers upon admission). Standard errors are clustered at the physician level.

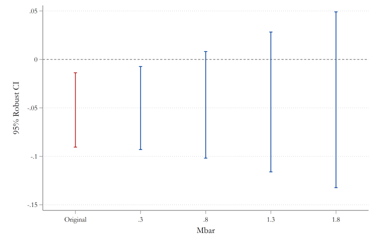
FIGURE A.3: HONEST DiD



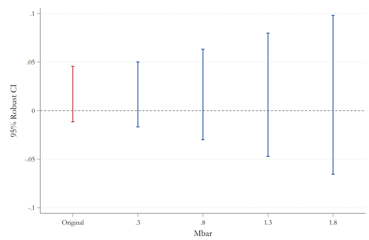
(a) Length of Stay



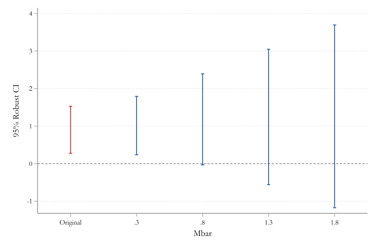
(b) Total Cost



(c) Hospitalization



(d) Reincidence



(e) Average Patient Satisfaction

Note: These figures display coefficients for sensitivity analysis before and after the treatment. It shows a robust confidence interval for different values of proportional violation of parallel trends assumption. The value equal to 1, for instance, imposes that the post–treatment violation of parallel trends is no longer than the worst pre–treatment violation of parallel trends (between consecutive periods). Likewise, a value of 2 implies that the post–treatment violation of parallel trends is no more than twice that in the pre–treatment period. Where the coefficients cross the zero line (breakdown value), it means that the significant result is robust to allowing for violations of parallel trends up to the value and as big as the max violation in the pre–treatment period.