The Effect of Communication and Transparency on Emergency Department Testing and Length of Stay*

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Abstract

Organisations typically solve problems with the inputs of many different experts, which requires timely communication between them. We estimate the effect of increasing the speed and transparency of internal communication on performance, in the Emergency Department of a leading hospital. Specifically, we study the effect of introducing a dashboard alerting that the results of the lab tests ordered have become available. We find that the introduction of this simple technology decreased the average length of stay in the ED by around 13%. A mediation analysis reveals that this decrease occurred largely through the channel of making doctors order less tests. Patient satisfaction increased and doctors were less likely to admit patients to the main hospital.

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1 Introduction

Human capital-intensive organisations such as hospitals leverage the skills of different experts in the joint dissection and resolution of problems (Garicano and Santos, 2004). An important case is the Emergency Department (ED), where patients are typically assigned a leading doctor who then often requires the help of other medical specialists, such as the laboratory scientists processing the tests that the doctor has ordered. Optimising both throughput and decision-making efficiency in settings such as the ED then requires organisations to set up and maintain systems of timely and transparent internal communication, so that the contributions of the different experts can reach the decision-makers quickly. Conversely, the absence of such systems will lead to avoidable bottlenecks and lengthy delays.

Large concerns abound about excessive waiting times and overcrowding in EDs. Waiting time is costly for patients, doctors, and the overall health system (Baumol, 2012, Woodworth and Holmes, 2020). More broadly, improving the efficiency of the healthcare sector is important given its continuing growth as a share of the GDP in both developed and developing economies. More research in ED is also important as scholars of the health sector have long argued that efficiency improvements in the way that healthcare is organised are possible yet elusive (Fuchs, 2004; Silver, 2020). Furthermore, increases in wages without the corresponding increases in productivity constitute one of the main challenges of the health sector (Baumol, 1967, 2012). While not the only factor, an important culprit for the increased waiting times in the ED is the sluggishness of internal communication between its different units. Furthermore, the sometimes lack of transparency in decision-making can potentially lead to suboptimal decisions, such as insufficient or excessive orders for laboratory tests.

The widespread adoption of information and communication technologies (ICT) in the last decades has improved organisations' ability to communicate faster and more transparently (Bloom et al., 2014). In settings such as the health industry, a natural prediction would be that better managerial practices would impact performance (Bloom et al., 2014, 2015, 2020, La Forgia, 2022). One such managerial practice is ICT adoption. Despite extensive literature documenting the potential effect of ICT (Almasi et al., 2021), econometric evidence convincingly estimating causal effects has lagged behind (Bronsoler et al., 2021).[1] Three

[1] At this respect, the medical literature tends to find more positive effects. See, for instance, Buntin et

major obstacles have precluded a full understanding of the causal effects of ICT adoption in the health industry. Firstly, the effects of ICT adoption sometimes occur at a relatively granular level, in which case detecting them requires rich administrative information at every stage of the diagnosis and treatment process. Secondly, ICT adoption is typically the result of other changes in the management of healthcare organisations, making identification challenging. Lastly, ICT are typically introduced as a bundle of technologies and practices, which makes it difficult to disentangle the separate effects of different technological tools.

In this paper, we study the introduction of a single, easy to understand, technological tool (i.e. a dashboard) that improved the communication between the technicians processing laboratory tests and the ED doctors using that information to diagnose and hospitalise or discharge patients. A secondary but important feature of this technology is that it increased the transparency of the tests ordered, such that an order by a specific doctor could be easily observed by other members of the medical staff. We take advantage of the fact that this dashboard was introduced in one of the two adult wards of the ED of a hospital (but not in the other) at a moment in time (July 2022) in which no other changes were introduced in the organisation. The dashboard automatically reflected the fact that the test results had become available, and was visually accessible to all members of the medical staff. We leverage access to rich administrative data and exploit a triple-differences strategy to estimate the effect of this dashboard on doctor actions and patient outcomes.

Our first contribution is to show that a relatively simple technology can have quantitatively large effects on the speed at which doctors deal with patients in the ED. Secondly, we show that the presence of the dashboard potentially affected other outcomes, such as patient satisfaction and admissions to the hospital. Lastly, and importantly, we show that the decrease in length of stay occurred partly through the channel of doctors ordering less (presumably unnecessary) tests.

Prior to July 2022, a doctor ordering a laboratory test for an ED patient in our hospital was not automatically informed when the results of the test became available. Instead, the doctor had to navigate a number of screens in the internal software system in order to check manually whether the result was ready. This process required entering the doctor's password

al. (2011) and Chaudhry et al. (2006).

and could not be delegated to a nurse. This informational friction was regarded as having two main direct consequences for doctors' ability to provide care. Firstly, frequent checking wasted doctors' time, a uniquely scarce resource in this setting. Secondly, infrequent checking meant that patients whose results were ready but not observed by the doctor remained in the ED for an inefficiently long time. In July 2022, a dashboard was placed in the station where the doctors and nurses operate from (see Figure 1). This dashboard automatically displayed the status of any test ordered from the ED and could be consulted visually by all of the doctors and nurses. Throughout the rest of the paper, we refer to the fact that the dashboard allowed doctors to be informed more quickly that their results were available as the 'faster communication of results'. A secondary unintended consequence of the dashboard is that it made all tests ordered by a specific doctor easily observable by other doctors and nurses in the ED. To the extent that doctors behave differently when their actions can be observed by others, the dashboard potentially affected the number of tests that doctors were willing to order.

The dashboard was installed only in one of the two adult wards in the hospital, permitting the use of a differences strategy (Chan, 2016). Using our preferred triple-differences strategy, we estimate that the introduction of the dashboard was associated with a large decrease (i.e. 13%) in the length of stay of the average patient. A leads and lags exercise indicates that the average length of stay evolved broadly similarly across the two wards in the months before July 2022, and then discontinuously decreased in the treated ward coinciding with the introduction of the dashboard.

We further estimate the effect of the dashboard on the number of laboratory tests that doctors ordered. Using again our baseline triple-differences specification, we find a statistically significant 10% decrease. We interpret this as evidence that the ED was characterised by a certain proportion of tests being ordered unnecessarily, and that the amount of 'overtesting' decreased when the tests ordered by a doctor could easily be observed by other doctors working in the ED (in a similar spirit as Sacarny et al. 2018, 2019). We find that the patterns of heterogeneity in the decrease in the number of tests ordered are consistent with this interpretation. Firstly, the decrease is larger for relatively common tests, which may be unnecessarily ordered as a default in some cases. Secondly, we find that it is less experienced doctors who decrease the tests ordered more strongly when these tests become more transparent. This is consistent with less experienced doctors being more concerned about their internal reputation and being willing to change their behaviour when their actions can be observed by others.

The decrease in the number of tests ordered posits the natural question of whether the decrease in length of stay is the exclusive result of lower number of tests (which mechanically decreases length of stay) or whether faster communication of results (holding constant the number of tests) is also quantitatively important. To disentangle these two mechanisms, we conduct a mediator analysis (Heckman and Pinto, 2015). We find that the decrease in the number of tests can account for around half of the decreased length of stay, with the other half being the result of faster communication of results.

The lower length of stay and reduced number of tests suggests that the introduction of the dashboard might have been associated with a lower average cost per patient. We confirm this with a triple-differences estimation in which the cost of diagnosis is the outcome variable. We find a 25% decrease in the average cost, following the introduction of the dashboard.

Next, we show that this decrease in cost is not at the expense of patient satisfaction. Rather the opposite: using the responses of a random sample of patients to a survey conducted by the hospital, we find a significant, albeit modest, improvement in patient satisfaction. This improvement might arise from spending less time in the ED and having to take less tests, especially if these tests involve syringes or other intrusive devices.

Lastly, we find that the introduction of the dashboard led to a lower likelihood that the patient is hospitalised (as opposed to discharged) after leaving the ED. In addition, there was no effect on the likelihood that the patient returns to the ED within a 30-day period. To the extent that these variables proxy for the health outcome of the patient, we conclude that the dashboard had either no effects or a positive effect on the patients treated in the ED.

Overall, we conclude that simple communication tools can have large impacts on the behaviour and efficiency of the ED. Part of this impact is intuitive, in that faster communication of results should naturally increase the speed at which patients are processed. However, another part is less expected, and follows from the fact that communication tools also often increase the amount of transparency associated with decision-making, and this has effects on how doctors choose to behave when others can observe their actions.

Contribution to the Literature We contribute to three strands of literature. First, we contribute to the literature studying how investment in ICT affects health outcomes (Devaraj and Kohli 2003, Buntin et al. 2011, Ganju et al. 2020, Ganju et al. 2021, Bronsoler et al. 2021). A pervasive feature of this literature is that it studies ICT adoption at the relatively aggregated level of the hospital (McCullough et al., 2016) or the region (Atasoy et al., 2018). By contrast, we leverage the granularity of our dataset and detailed knowledge about the institutional environment to examine the effect of a single ICT tool at a very disaggregated level. More broadly, our paper is related to the growing body of literature in managerial economics showing the relevance of communication for productivity in the workplace (Englmaier et al. , 2016). For instance Menzel (2021) and Sandvik et al. (2020) study experiments that encourage workers to share their knowledge. Our proposal is instead to study a setting in which a technological shock improves the intra-organisational communication of information. In this respect, our study is most related to Battiston et al. (2020), who study how the ability to communicate face to face improves productivity.

Second, a large body of work in health economics (Chan 2016, 2018, Silver 2020, Woodworth and Holmes 2020, Chan and Chen 2022, Gruber et al. 2023) and healthcare management (Freeman et al. 2021, Gowrisankaran et al. 2022, Adepoju et al. 2023) studies the determinants of productivity and costs in the ED. Similar to these studies we rely on data from the ED but different from them we study a quasi-experiment in which a technological tool affected one part but not the other part of the hospital.

Lastly, our paper contributes to the identification of mechanisms to decrease overtesting in hospital settings (for a review of this literature, see Tam 2022). Most contributions have focused on interventions explicitly tailored to prevent unnecessary laboratory orders, such as educational feedback (Miyakis et al., 2006), automated alerts indicating order mistakes (Levick et al., 2013), tweaks to the care provider order software (Neilson et al., 2004), and computerised reminders (Bates et al., 1999). The intervention that we study in this paper is simpler and less effort-intensive than previous ones. We find that simply by increasing the transparency of orders, a significant reduction in the number of orders can be organically achieved.

Plan Section 2 describes the institutional setting. Section 3 describes the main hypotheses in the study. Section 4 outlines our empirical strategy. In section 5 we present the main results on the length of stay variable. In sections 6-8 we present the results on other dependent variables. Section 9 concludes.

2 Institutional Setting

In this section, we briefly describe the overall functioning of the ED, and explain the potential bottleneck arising from the protracted communication of the laboratory results.

The Emergency Department Our study takes place in the ED of the Fundación Valle del Lili (henceforth FVL) Hospital. The FVL hospital is a not-for-profit general teaching hospital located in Cali, Colombia. FVL was ranked 149th in the world in the 2022 edition of The World's Best Hospitals (Newsweek, 2022). In 2021, the hospital comprised of 680 beds and 20 operating rooms, and hired 724 doctors. With these resources, the hospital processed around half a million outpatient visits and 36,000 hospital discharges, and performed 300 transplants.

The FVL ED operates similarly to the EDs in other hospitals around 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 checks for insurance eligibility to be admitted at FVL. Eligible patients are then seen by a nurse.[2] Patients with conditions requiring admittance to the ED are then triaged and assigned to one of two wards depending on their triage level and insurance status, as follows. Patients with a standard insurance coverage and triage levels 1-3 are sent to the 'regular' ward.

[2]Patients arriving by ambulance after a car accident, a heart attack or a similarly critical condition skip this step and are sent directly to the resuscitation room. Once they are stable, they are sent to the intensive care unit. This is independent of insurance status.

Patients with additional private insurance coverage are sent to the 'private insurance' ward independently of triage level.[3]

After arrival to the corresponding 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' doctor that becomes available (there are several such doctors working in parallel). In the consulting room, this doctor gathers additional information, potentially orders laboratory tests and performs an initial diagnosis. The patient is then sent to a bed for observation and is put under the care of a potentially different doctor. This 'ward' doctor reviews the information, periodically observes the evolution of the patient and incorporates the information from the laboratory test results when these become available and are communicated to her. At regular intervals, the ward doctor decides between: (a) keeping the patient in the ward for longer, (b) discharging him, and (c) admitting him to the non-ED wing of the hospital.

The Test Results Communication Bottleneck An important objective in the FVL ED is to gather and process information about patients condition as quickly as possible, for two main reasons. Firstly, patients in need of urgent treatment will benefit from receiving this treatment promptly. Secondly, a swift diagnosis will typically decrease the length of stay in the ED regardless of health condition, increasing patient satisfaction, relieving pressure on ED capacity and reducing costs. Making a prompt diagnosis naturally requires the information generated by the different health professionals to reach the decision-maker (in our case, the ward doctor) quickly. When a laboratory test has been ordered, unnecessary delays may arise if the ward doctor is not rapidly informed when the test result becomes available.

Prior to the installation of the test results dashboard, ward doctors had to manually log into the internal software system and navigate a number of screens in order to check whether a result had become available. Searches were individual, in that a doctor inquiring for the

[3]Two types of patients are dismissed: (a) patients with no triage level because their condition does not require admission to the ED, and (b) regular package patients with triage levels 4-5 who are sent to a different hospital.

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 ward nurse, as it required entering the doctor's password. The system imposed unnecessary burdens on ward doctors and it had two potential consequences. Firstly, the system inquiries directly used doctors' valuable time and detracted from the provision of direct patient care. Many of these inquiries were wasted, as they showed that the test results were yet unavailable. Secondly, patients whose results were available and could potentially have been treated, discharged or hospitalised, would remain on hold until the ward doctor decided to inquire in the software system.

The Test Results Dashboard In 2022, FVL decided to alleviate this information bottleneck by providing doctors with immediate salient information about the state of each laboratory test. In partnership with a provider of software services, a test results dashboard was placed in the doctors and nurses station.[4] In consultation with the authors of this study, the dashboard was placed only in the private insurance ward, but not in the regular ward. The dashboard could be visually consulted at all times by any nearby staff member, but was hidden from patients and relatives.

Figure 1 displays a screenshot of the test results dashboard. Each row represents a set of tests involving a patient, ordered at a specific moment in time. In addition to the order and patient numbers, the dashboard contains a column for each potential type of test (e.g. blood, endocrinology...). Cells are empty if the corresponding test type was not part of the order set, and filled with a circle if it was. White circles depict tests that are not yet available. Blue circles show that the results are ready but are in process of validation. Green circles depict available results that fall within pre-established standard intervals. Following a traffic light system, results outside these intervals are depicted in either yellow (i.e. concerning) or red (i.e. critical). Learning the actual numerical values of the test results continued to require logging into the system with the doctor's password.[5]

[4]The software and hardware package comprising the dashboard could not be purchased in the open market, at least in the context of Colombia in 2022. To the best of our knowledge, only one other Colombian hospital used this package in 2022.

[5]Throughout our sample period, the technicians in the laboratory would typically phone the ED immediately if the test results indicated the need for urgent action (e.g. if they were in the critical range). This

The dashboard was installed in the third week of June 2022. Over the following two weeks, doctors were informed and trained about its use. For this reason, we take July 2022 as a first month in which the dashboard was active and all doctors were theoretically able to take advantage of it. Unfortunately, the dashboard ceased to be used around September, as the doctors in charge became increasingly skeptical about its usefulness.

Overtesting and Transparency Commonly to other medical settings, the FVL ED is characterised by the perception that (some) doctors engage in overtesting. Specifically, our conversations with senior members of the ED team suggest that some doctors order a battery of standard tests as a default measure, without sometimes pausing to consider whether these tests justify the associated cost and increased patient length of stay. This is of course just a perception, as it is exceedingly difficult to judge from the outside whether a specific test order was warranted by the information available to the doctor. It is this difficulty that prevents senior management from systematically measuring and evaluating doctors relative to a 'standard' number of ideal tests per patient. Naturally, prior to the introduction of the dashboard, the ordered tests were private information to the ordering doctor: other medical staff would not typically and easily be able to observe how many and which tests a doctor had ordered.

The installation of the dashboard increased the transparency of the test ordering process. In particular, the salience of the dashboard in the staff area implied that any member of staff could observe the tests being ordered, at least until the results came back and the icons disappeared from the dashboard. We hypothesise below that this increased transparency might have caused doctors to rein any unnecessary tests.[6]

custom did not change after July 2022.

[6]The dashboard did not provide information on patients' health status. If the tool provided this information is possible that some inexperienced doctors try to order the same battery of test for their own patients that more experience doctors ordered for their patients when both sets of patients' characteristics are similar.

3 Hypotheses

Our starting hypothesis is that enhancing the speed of communication between the test laboratory and the ED doctor should decrease the time that patients spend in the ED. As discussed above, the main rationale is that doctors are typically very busy in the ED, and having to log in and enter a password to personally find out whether the results are available generates unnecessary bottlenecks and delays the discharge of patients. In this context, the introduction of a technology that automatically displays the results as they become ready and can be consulted by both doctors and nurses should accelerate the processing of patients.

Hypothesis 1: *The introduction of the dashboard should be associated with a lower average length of stay in the ED.*

In order to understand our second hypothesis, remember that in addition to displaying the availability of the test results (as they become available) the dashboard also displays the fact that tests have been ordered for a specific patient. The result is to increase the transparency of the test orders. Consider the calculation of a doctor evaluating whether to order an additional test. The obvious benefit is the (in some cases small) chance that the test might uncover important information and therefore dramatically improve the diagnosis that the doctor is able to make. The doctor would benefit from this both from a reputational perspective (making the right diagnosis signals high ability and can enhance the doctor's professional career) and from the perspective of internalising the patient's welfare. The cost of ordering an additional test is that tests are expensive, both from a financial and time-usage perspective. To the extent that the doctor does not fully internalise these costs, the marginal test ordered will be of negative value from a cost-benefit perspective. As a result, there will be overtesting.

The calculation that we have outlined above would characterise a doctor operating under opaque conditions (i.e. colleagues cannot observe how many tests the doctor ordered). If test orders are fully transparent to everybody, an additional reputational cost may be paid by doctors who are perceived to regularly overtest. In turn, this may lead doctors to decrease or even eliminate the amount of overtesting. The prediction is therefore that an increase in the transparency of the tests being ordered would lead to a lower number of tests.

Hypothesis 2: *The introduction of the dashboard should be associated with less tests being ordered.*

Note that a potential decrease in the number of tests being ordered would further reinforce our prediction in Hypothesis 1. If the transparency of the tests ordered (associated with the introduction of the dashboard) leads to a decrease in the number of tests, patients will on average spend less time in the ED.

The effect underlying Hypothesis 2 might not be homogenous across types of doctors and tests. For instance, less experienced doctors might be more affected by the introduction of the dashboard. Unexperienced doctors might be both less confident in their initial diagnosis and more interested in signalling high ability, which would make them more prone to overtesting. As a result, unexperienced doctors might curb more their test orders when their tests become easily observable by colleagues.

Another type of heterogeneity that we might expect refers to the type of tests. Some laboratory tests are relatively obscure, and doctors are unlikely to order them without a strong belief that they will probably shed light on a specific diagnosis that is being suspected. Other tests are very common, and often ordered as a default. Our discussions with senior doctors in the ED indicate that it is this second type of tests that are more likely to be associated with overtesting.

In terms of the characteristics of the patients, it is plausible that tests ordered for relatively young and healthy patients are more likely to be unnecessary, whereas old and frail patients are not subject to the same amount of overtesting. We therefore posit that it may be relatively younger patients that experience a higher decrease in the number of tests ordered following the introduction of the dashboard.

Lastly, we posit that doctors who on average ordered a lot of tests prior to the introduction to the dashboard should be more likely to decrease their orders afterwards, as they are more likely to have been engaging in overtesting.

Hypothesis 3: *The effect of the dashboard on the number of tests should be stronger for: (a) inexperienced doctors, (b) types of tests that are ordered very frequently, (c) younger patients, and (d) doctors who prior to the introduction of the dashboard were ordering lots* *of tests.*

Our last hypothesis is that the introduction of the dashboard should translate into positive patient outcomes, most directly patient satisfaction with the overall functioning of the ED. Our rationale to make this prediction follows from hypotheses 1 and 2. Specifically, patients should appreciate the decrease in length of stay following the introduction of the dashboard. To the extent that the time that doctors were spending checking whether the results were available can now be redirected to patient care, satisfaction with the ED should also increase. Lastly, the decrease in the number of tests being ordered should also leave patients better off, in an environment in which overtesting is prevalent and the marginal test is of little diagnostic value.

Hypothesis 4: *The introduction of the dashboard should be associated with higher average patient satisfaction.*

Lastly, we note that we do not have strong priors about the likely effect of the dashboard introduction on the other dependent variables that we study in this paper (as there are arguments in favor and against a decrease): (a) the likelihood of hospitalisation (as opposed to discharge) and (b) the 30-day return of the patient to the ED.

We test these hypotheses in the remaining sections of the paper.

4 Empirical Strategy and Data

In this section we outline our baseline empirical strategy and discuss the rationale behind the use of a triple-differences specification.

Differences-in-Differences Our initial empirical strategy is a differences-in-differences (DiD) specification. Cases assigned to the private insurance ward, in which the dashboard was operational from July 2022, comprise the treatment group. Cases assigned to the regular ward, in which the informational dashboard was never set up, represent the control group. Specifically, we estimate:

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

where y_i is an outcome (such as length of stay) of case i, $w(i)$ indexes the ward to which patient i is assigned, $d(i)$ indexes the doctor allocated to patient i, and $t(i)$ indexes the exact hour (i.e. date and hour of day combination) in which patient i arrived to the ED. $Private_{w(i)} = 1$ for the private ward and $Post_{t(i)} = 1$ for the post-July period. The model controls for doctor $\alpha_{d(i)}$, ward $\theta_{w(i)}$ and hour $\pi_{t(i)}$ fixed effects, as well as patient pre-determined characteristics $\mathbf{X_i}$ (patient age and gender, triage level, main diagnosis and patient vital signs on arrival to the ED).[7] The parameter β captures the average differential outcome for cases assigned to the private insurance ward following the introduction of the dashboard.

Triple-Differences Strategy In the context of EDs, the exploitation of organisational changes to one hospital ward while using a different ward as a control group in a DiD strategy was pioneered by Chan (2016).[8] 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 dashboard.

A challenge in our setting is that, according to our discussions with FVL administrators and doctors, the introduction of the dashboard 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.[9] In order to alleviate this concern, 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.[10] Specifically,

[7] Instead of controlling for the ward to which the patient is assigned, we control more finely for the detailed insurance company of the patient. Because the insurance company fully determines the ward, the insurance company fixed effects subsume the ward fixed effects.

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

[9] 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 doctor fixed effects included in the regression. We have no anecdotal evidence that this is indeed the case, but it might be a potential concern.

[10] We choose the year 2019 as it is the last pre-COVID year. In 2020 and 2021 multiple changes to

we pool the 2019 and 2022 March-October months together in the sample and use as main independent variable of interest the triple interaction between $(Private_{w(i)} \times Post_{t(i)})$ and a year 2022 dummy. The model becomes:

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

In this triple-differences model all the control variables are interacted with the year 2022 dummy. The triple-differences model studies the differential effect in outcome y_i in the private ward relative to the regular ward, in the post-July period relative to the pre-July period and in 2022 relative to 2019.

Event Study Analysis The standard test of the identification assumption in the differences framework is the evaluation of potential differential pre-trends. We evaluate these pre-trends using the following leads and lags model:

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

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 information dashboard, and $\hat{\beta}_1, ..., \hat{\beta}_K$ capture the corresponding effects for the K months following the introduction in July 2022.[11]

Descriptive Statistics Our main analysis sample comprises of eight months centered around the introduction of the dashboard in July 2022, and their equivalent in 2019. The

the internal physical organisation of the ED (including the temporary elimination of the private insurance ward) make comparisons difficult. We provide evidence that choosing 2018 instead would generate very similar estimates. We also provide results using the double-differences DiD specification in the Appendix. Specifically, Tables A1-A3 are the double-differences equivalent of Tables 2, 4, 6.

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

64, 152 cases in our sample include 43, 607 distinct patients cared for by 387 distinct doctors. Table 1 displays summary statistics for the main variables in the study. In terms of the outcome variables, the length of stay variable is right skewed, as it has a mean of .55 days, which is well above the .22 median (approximately 5 hours). Similarly the median case requires 3 tests and the average is 6.29. 25% of patients are hospitalised, and 13% return within 30 days to the ED.

The private insurance ward and the regular ward deal with a broadly similar number of cases. Because the number of cases is broadly similar in every month of the sample, the post June dummy takes an average of .51.

5 Length of Stay

In this section we display the results of testing Hypothesis 1, which predicts that the introduction of the dashboard should decrease average length of stay. This stay is computed from the moment the patient arrives to the ED to the moment she leaves it (i.e. we do not consider any length prior or after the ED visit). Length of stay is an important measure of input intensity (Silver, 2020) and organisational performance (Chan, 2016, 2018; Chan and Chen, 2022).

Baseline Results Table 2 displays the baseline results from estimating (1) and (2). The DiD model centred around July 2022 suggests in Column 1 that the introduction of the information dashboard is associated with a 25% decrease in the average case length of stay. This very large estimate is consistent with the delayed communication of tests results to doctors generating an economically significant bottleneck in the processing of patients. In Column 2, we however caveat the above finding. We repeat the estimation of (1) but using the 'placebo' year of 2019, in which no information dashboard was introduced at any point. We find that the post-June period was associated with a decrease in length of stay of around 12%. 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.

In Column 3, we display the results of our preferred triple-differences model. We find an estimate of around -13%. Throughout the rest of the paper we continue to use the triple-differences model as our baseline estimation. The estimates from the double-differences model can be found in the appendix.

To summarise, this subsection displays preliminary suggestive evidence that the introduction of the dashboard led to a decrease in the length of stay. As outlined above, two potential mechanisms are consistent with this decrease: (a) every test result was communicated and processed more quickly, and (b) the increase transparency of tests led to a lower number of tests ordered. At this point, we cannot distinguish between these two explanations.

Leads and Lags Analysis We display in Figure 2A the estimates of (3). We find that the differential effect of being assigned to the private insurance ward remains broadly constant in the months leading to the introduction of the dashboard. The first full month after this introduction, a discontinuous decrease in length of stay of around 13% is apparent in the figure. The estimate decreases to about 20% in August and then reverts back to initial levels. Overall, we interpret the evidence in Figure 2A as largely supportive of the main identification strategy in the paper. The figure also reveals that availability of the dashboard ceased to decrease length of stay after a couple of months, coinciding with our anecdotal evidence that doctors stopped turning on the dashboard around that time.

Robustness In Table 3 we evaluate the robustness of our estimates to the set of control variables introduced in the baseline specification. We start in Column 1 with a completely streamlined model, which only controls for a post dummy and a private insurance ward dummy (both interacted with the year 2022 dummy). In Column 2 we introduce insurance status and hour fixed effects. In Column 3 we add the initial consultation doctor fixed effects. Relative to Column 3, we add patient controls in Column 6, interacted with the year 2022 dummy. Column 6 represents our baseline model, with the full sample and the most extensive set of controls. Throughout we find that even after our very extensive set of controls, the introduction of the dashboard continues to be associated with a large decrease in the average length of stay. The coefficient decreases from $-.25$ (in the streamlined model) to $-.13$ (in the full model), but remains highly statistically significant throughout. Table A1 shows that the estimates evolve in a similar way if we conduct a double difference model instead.

In Column 4 we further explore the robustness in the Column 6 baseline estimates. We winsorise the top 10% of the length of stay values. While converting this dependent variable into logs should have alleviated the strong skewness of the length of stay distribution, winsorising the top part of the distribution contributes to reassure us that the baseline estimates are not disproportionately due to extreme positive values. We find broadly similar estimates.

In Column 5 we drop Triage 4 and 5 cases from the sample. 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. Again, we find that the DiDiD estimate remains broadly similar.

6 Number of Tests

In this section we investigate whether the introduction of the dashboard led to doctors ordering less tests.

Baseline Effects We first estimate this effect by replicating our baseline specification but using the (log plus one) number of tests as outcome variable. We find in Column 1 Table 4 a negative and highly statistically significant coefficient. On average, the number of tests ordered decreased by 10% following the introduction of the dashboard. This finding supports Hypothesis 2, confirming that the increased transparency of the tests ordered may have decreased the amount of overtesting.

We confirm this finding in Panel B Figure 2, where we find that the number of tests ordered remained broadly unchanged in the months leading to the introduction of the dashboard, and then decreased around 15% in August 2022. Consistently with the equivalent figure for length of stay, the effect seems to revert back to its initial levels after three months.

The remarkable similarity in the evolution of the length of stay and number of tests ordered suggest that a decrease in the number of tests may have been the main mechanism causing the length of stay to decrease, following the introduction of the dashboard.

Mechanisms for the Decrease in Length of Stay The finding that both the length of stay and the number of tests ordered decreased begets the question of what are the mechanisms through which the introduction of the dashboard led to a decrease in the length of stay. Our initial assumption was that being informed more rapidly that the test results are available allows doctors to reach a diagnosis more quickly and discharge or hospitalised patients faster. However, we have posited as a secondary hypothesis that the decrease in the number of tests documented in this section might have independently decreased the length of stay, as doctors do not wait for that additional result or opinion to reach a conclusion. The next natural question is whether the length of stay decrease is the exclusive result of fewer tests being ordered.

Identifying the quantitative importance of different mechanisms is a notoriously difficult exercise, but in this subsection we examine whether any share in the decrease in the length of stay is independent of the effects on the number of tests. Firstly, we estimate (2) while controlling for the number of tests ordered. We display the results in Column 4 Table 2. We find there that the baseline DiDiD 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.

While enlightening, we acknowledge that the evidence in Column 4 Table 2 can at best only be regarded as suggestive, given that the regressions are controlling for explicitly endogenous variables. To be more systematic, 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 dashboard and X_i is a set of controls. The method decomposes the effect of the treatment into two parts:

$$\frac{dy}{dT} = \frac{\partial y}{\partial M}\frac{\partial M}{\partial T} + R \tag{4}$$

where M is the mediator. From (4) 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%. This implies that around 52% of the effect is independent of the mediating variable. Overall, we conclude that around half of the decrease in the length of stay is due to the increased transparency of tests leading to a lower number of them.

Heterogeneity of the Effects In Columns 4, 5 from Table 4, we disaggregate the number of tests ordered into types of tests that are more or less frequent. We find a much larger coefficient for relatively frequent tests (i.e. ordered at least as frequently as the median test), which might be sometimes ordered without sufficient consideration for the financial and time cost associated with the tests. On the other hand, relatively infrequent tests are not statistically affected by the introduction of the dashboard. This is consistent with hypothesis 3.

In Columns 8, 9 from Table 4, we split the sample on the basis of the experience of the doctor in the FVL ED. We find that both types of doctors decreased the number of tests ordered following the introduction of the dashboard. However, the effect is much stronger for relatively less experienced doctors (i.e. below the median). Again, this confirms our prediction in hypothesis 3.

In Columns 2, 3 from Table 4, we split the sample by the type of doctor, specifically in terms of the propensity of the doctor to order tests. To do this, we calculate the number of tests that doctors order prior to the introduction of the dashboard, and then estimate the baseline model separately for above-median and below-median doctors. Suprisingly, we find that it is below-median doctors that are affected more strongly by the introduction of the dashboard. This is suprising because we would expect that above-median doctors engage more in overtesting, and therefore should curb more the number of tests ordered following the introduction of the dashboard.

Lastly, in Columns 6, 7 from Table 4 we present results differentiating between relatively young and old patients. We find that the decrease in the number of tests is present for below-median patients (in terms of their age) but note above-median patients. This is consistent with our hypothesis that the share of tests that are unnecessary is higher for younger patients.

7 Patient Satisfaction

In this section, we examine whether the introduction of the dashboard improved patient satisfaction with the care provided in the private insurance ward, relative to the regular ward. Our hypothesis is that decreased length of stay and decreased number of (unnecessary) tests may translate into patient being more satisfied with the ED.

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 doctor complied with good medical practices, and (3) whether the patient believed that the doctor was good at answering questions and addressing potential concerns.[12] Unfortunately, we only have these survey results for the year 2022 and a relatively small sample size of fewer than two thousand observations. As a result, the specification in this subsection is a DiD model (with coarser time effects) and the leads and lags regressions are a bit noisy.

Table 5 displays the results. We find that the introduction of the dashboard had positive effects on patient satisfaction for all the three measures. In terms of magnitude the improvement in 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 regress the average of the three questions and find qualitatively similar results. The effects are large in magnitude,

[12] 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.

which illustrates how arguably simple and cheap technological tools can have a meaningful impact on the way that patients feel about the hospital service.

In Figure 5, we plot the estimated leads and lags from (3). We find that patient satisfaction is not trending in any direction prior to July 2022, after which there is a meaningful improvement in all three measures as well as the average. While the estimates are a bit noisy, we interpret the broad findings in this section as providing suggestive evidence in support of Hypothesis 4.

8 Effects on Other Variables

In Table 6 we display the effects of the introduction of the dashboard on a variety of additional dependent variables. Firstly, we find in Column 1 that the installation of the dashboard had no effect on the likelihood that the patient returns to the ED in the next month. In Column 2 we instead find a large effect on the likelihood that the patient is transferred to the non-ED wing of the hospital, as opposed to being discharged home. The decrease in this likelihood is around 7 percentage points, which represents around 27% of the unconditional likelihood. We confirm this finding in Figure 3 Panel B, which shows a discontinuous decrease in this likelihood after July 2022. To the extent that admission to the hospital represents an acknowledgment that the patient has not improved sufficiently during her stay at the ED, we can conclude that the installation of the dashboard improved patient outcomes (perhaps from the increase in the speed of tests communication). In turn, this decrease in the hospital admission might represent an additional factor explaining the improvement in patient satisfaction that we documented in Table 5. Table A3 shows similar effects when we use the double-difference model.

In Column 3 Table 6, we create a variable comprising of the total cost of the diagnostic tools associated with a specific case. This total cost variable incorporates the type (as well as the number) of tests. We find that this total cost variable decreased by around 25% following the introduction of the dashboard. This effect is quite remarkable as the 25% estimate is far above the 10% estimate for the number of tests, suggesting that it was relatively more expensive tests that were eliminated as a result of the increased transparency of tests.

Lastly, we investigate whether the lab technicians might have altered the speed at which they process the required tests. While we do not have a strong hypothesis that this might have been the case, this possibility would provide an alternative mechanism for the decrease in length of stay, which we want to rule out. In Column 4 Table 6 we estimate (2) using the time that the average test takes to be processed as the dependent variable (naturally, the sample contains only cases in which at least one test was ordered). We find that the introduction of the dashboard did not have an effect on this variable.

9 Conclusion

We have found that a relatively simple technological tool had large effects on the throughput, diagnostic inputs and (potentially) health outcomes in the ED of a leading hospital. The main channel through which this tool impacted behaviour and performance in the ED was, however, in decreasing the number of tests requested and consultations with specialists. A potential explanation is that doctors were requesting too many of these additional diagnosis inputs, and the visibility of the dashboard prompted a reconsideration in the optimal number of requests. Overall, the fact that the decrease in the length of stay took place through this channel highlights that the introduction of new technologies can lead to unexpected responses in the behaviour of organisational actors.

Adepoju, T., Carson, A. L., Jin, H. S., and Manasseh, C. S. (2023). "Hospital Boarding Crises: The Impact of Urgent vs. Prevention Responses on Length of Stay.", *Management Science*.

Almasi, S., Raibel, R., Moghaddasi. H., and Vahidi-Asi, M. (2021). "Emergency Department Quality Dashboard; a Systematic Review of Performance Indicators, Functionalities and Challenges.", *Archives of Academic Emergency Medicine*, 9(1): 1-11.

Atasoy, H., Chen, P. Y., and Ganju, K. (2018). "The spillover effects of health IT investments on regional healthcare costs.", *Management Science*, 64(6): 2515-2534.

Bates, D. W., Kuperman, G. J., Rittenberg, E., Teich, J. M., Fiskio, J., Ma'luf, N., ... and Tanasijevic, M. (1999). "A randomized trial of a computer-based intervention to reduce utilization of redundant laboratory tests.", *American Journal of Medicine*, 106(2): 144-150.

Battiston, D., Blanes i Vidal, J., and Kirchmaier, T. (2020). "Face-to-Face Communication in Organizations.", *Review of Economic Studies*, 88(2): 574-609.

Baumol, W. J. (1967)."Macroeconomics of unbalanced growth: the anatomy of urban crisis.", *American Economic Review*, 57(3): 415-426.

Baumol, W. J. (2012)."The Cost Disease: Why Computers Get Cheaper and Health Care Doesn't.", *Yale University Press.*

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.*

Bloom, N., Gawande, A., Huckman, R., Jha, A., Sadun, R and Tsai T.

(2015). "Hospital Board And Management Practices Are Strongly Related To Hospital Performance On Clinical Quality Metrics", *Health Affairs, 34 (8): 1304-1311.*

Bloom, N., Lemos, R., Sadun, R. and Van Reenen, J. (2020). "Healthy Business? Managerial Education and Management in Healthcare", *Review of Economics and Statistics, 102 (3): 506-517.*

Bronsoler, A., Doyle, Joseph J,J., and Van Reenen, J. (2021). "The impact of healthcare it on clinical quality, productivity and workers", *Working Paper 29218, National Bureau of Economic Research.*

Buntin, M. B., Burke, M. F., Hoaglin, M. C., and Blumenthal, D. (2011). "The benefits of health information technology: A review of the recent literature shows predominantly positive results. ", *Health Affairs*, 30(3): 464–471.

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.*

Chaudhry, B., Wang, J., Wu, S., Maglione, M., Mojica, W., Roth, E., Morton, S. C., and Shekelle, P. G. (2006). "Systematic review: Impact of health information technology on quality, efficiency, and costs of medical care. ", *Ann. Internal Medicine*, 144(10): 742–752.

Devaraj, S. and Kohli, R. (2003). "Performance impacts of information technology:

Is actual usage the missing link?.", *Management Science*, 49(3): 273-289.

Englmaier, F., Roider, A. , and Sunde, U. (2016). "The Role of Communication of Performance Schemes: Evidence from a Field Experiment." *Management Science*, 63(12): 3999-4446.

Freeman, M., Robinson, S., and Scholtes, S. (2021). "Gatekeeping, fast and slow: An empirical study of referral errors in the emergency department." *Management Science*, 67(7): 4209-4232.

Fuchs, V.R. (2004). "More Variation In Use of Care, More Flat-Of-The Curve Medicine.", *Health Affairs*, 23(Suppl2):VAR-104-VAR-107.

Ganju, K., Atasoy, H., McCullough, J., and Greenwood, B. (2020). "The Role of Decision Support Systems in Attenuating Racial Biases in Healthcare Delivery", *Management Science*, 66(11): 4921-5484.

Ganju, K., Atasoy, H. and Pavlou, P. (2021). "Do Electronic Health Record Systems Increase Medicare Reimbursements? The Moderating Effect of the Recovery Audit Program.", *Management Science*, 68(4): 2377-3174.

Garicano, L. and Santos, T. (2004). "Referrals.", *American Economic Review*, 94(3): 499-525.

Gowrisankaran, G., Joiner, K., and Pierre, T.L. (2022). "Physician practice style and healthcare costs: Evidence from emergency departments.", *Forthcoming, Management Science*.

Gruber, J., Hoe, T.P., and Stoye, G. (2023). "Saving Lifes by Tying Hands: The Unexpected Effects of Constraining Health Care Providers.", *Review of Economics and*

Statistics, 105(1): 1-19.

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.

La Forgia, A. (2022). "The Impact of Management on Clinical Performance: Evidence from Physician Practice Management Companies", *Management Science*, Forthcoming.

Levick, D. L., Stern, G., Meyerhoefer, C. D., Levick, A., and Pucklavage, D. (2013). "Reducing unnecessary testing in a CPOE system through implementation of a targeted CDS intervention." *BMC Medical Informatics and Decision Making*, 13: 1-7.

Mazor, L., Heart, T., and Even, A. (2016). "Stimulating the Impact of an Online Digital Dashboard in Emergency Departments on Patients Length of Stay.", *Journal of Decision Systems*, 21(1): 343-353.

McCullough, J. S., Parente, S. T., and Town, R. (2016). "Health information technology and patient outcomes: the role of information and labor coordination.", *RAND Journal of Economics*, 47(1): 207-236.

Menzel, A. (2021). "Knowledge Exchange and Productivity Spill-overs in Bangladeshi Garment Factories.", *Journal of Economic Behavior Organization*, 185: 721-746.

Miyakis, S., Karamanof, G., Liontos, M., and Mountokalakis, T. D. (2006). "Factors contributing to inappropriate ordering of tests in an academic medical department and the effect of an educational feedback strategy. " *Postgraduate Medical Journal*, 82(974): 823-829.

Neilson, E. G., Johnson, K. B., Rosenbloom, S. T., Dupont, W. D., Talbert, D., Giuse, D. A., ... and Resource Utilization Committee*. (2004). "The impact of peer management on test-ordering behavior." *Annals of Internal Medicine*, 141(3): 196-204.

Sandvik, J. J., Saouma, R. E., Seegert, N. T., and Stanton, C. T. (2020). "Workplace Knowledge Flows", *Quarterly Journal of Economics*, 135(3): 1635-1680.

Sacarny, A.,Barnett, M., Jackson Le, P., Tetkoski R., Yokum, D., and Agrawal, S. (2018). "Effect of Peer Comparison Letters for High-Volume Primary Care Prescribers of Quetiapine in Older and Disabled Adults A Randomized Clinical Trial", *JAMA Psychiatry*, 75(10): 1003-1011.

Sacarny, A., Olenski, A., and Barnett, M. (2019). "Association of Quetiapine Overuse Letters With Prescribing by Physician Peers of Targeted Recipients A Secondary Analysis of a Randomized Clinical Trial", *JAMA Psychiatry*, 76(10): 1094-1095.

Silver, D. (2020). "Haste or Waste? Peer Pressure and Productivity in the Emergency Department.", *Review of Economic Studies*, 88(3): 1385-1417.

Tam, E. (2022). "Methods to Reduce Medical Over-testing of Patients." *Intersect: The Stanford Journal of Science, Technology, and Society*, 15(2): 1-14.

Woodworth, L. and Holmes, J. F. (2020). "Just a Minute: The Effect of Emergency Department Wait Time on the Cost of Care", *Economic Inquiry*, 58(2): 698-716.

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
30-Day Return Dummy	.13	.34	0	0	0	0	1
Hospital Admission Dummy	.25	.43	0	0	0	0	1
Independent Variables:							
Private Ward Dummy	.59	.49	0	0	1	1	1
Post June Dummy	.51	.5	0	0	1	1	1
Selected Control Variables:							
Male Patient Dummy	.42	.49	0	0	0	1	1
Patient Age	47.47	19.29	23	31	45	62	75
Triage 1 Dummy	.05	.22	0	0	0	0	0
Triage 2 Dummy	.25	.44	0	0	0	1	1
Triage 3 Dummy	.37	.48	0	0	0	1	1
Triage 4 Dummy	.3	.5	0	0	0	1	1

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. 30-day return dummy takes value one if the patient returned to the ED within 30 days. Hospital admission dummy takes value one if the patient was admitted to the hospital instead of discharged home.

TABLE 2 - 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***	-.113***	-.093***
	(.043)	(.026)	(.026)	(.019)
Post June X Private Ward X Year 2022			-.131***	-.053
			(.051)	(.033)
Log Number of Tests				.776***
				(.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	61,628	61,628

This Table displays estimates of regressions of a case's length of stay in the ED on the period during which the dashboard 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 to the ED. The estimating equation in Column 1 is:

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

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 doctor to which the patient was assigned. 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), doctor and hour fixed effects, as well as patient controls (age, gender, main diagnosis and vital signs markers upon admission). In Column 2 we repeat the Column 1 exercise on the placebo sample of 2019. In Columns 3, 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 interations between all the controls and the year 2022 dummy. Standard errors are clustered at the doctor level.

TABLE 3 - ROBUSTNESS EXERCISES TRIPLE-DIFFERENCES MODEL

Dependent Variable = Log Length of Stay	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Post June X Private Ward X Year 2022	-.254***	-.383***	-.354***	-.162***	-.124**	-.131***
	(.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	61,640	62,648	40,862	61,628

This Table displays estimates of regressions of a case's length of stay in the ED on the period during which the dashboard 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 to the ED. The estimating equation in Column 4 is:

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

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 doctor 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), doctor and hour fixed effects, as well as patient controls (age, gender, main diagnosis and vital signs markers upon admission). 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. In Column 2 we include the insurance status and the hour fixed effects (which subsume the year 2022 and private ward dummies). In Column 3 we add the doctor fixed effects. In Column 4 we add the patient controls and the top 10% of the length of stay distribution is winsorised. In Column 5 we add the patient controls and the sample includes only triage levels 1-3. Column 6 is the baseline model. All the patient controls are interacted with the year 2022 dummy. Standard errors are clustered at the doctor level.

TABLE 4 - EFFECTS ON LABORATORY TESTS
TRIPLE-DIFFERENCES MODEL

Dependent Variable = Log Number of Tests

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Log Number Tests	**Pre-Period Tests**		**Frequency Tests**		**Patient Age**		**Doctor Experience**	
		Low	**High**	**Low**	**High**	**Young**	**Old**	**Low**	**High**
Post June X Private Ward X Year 2022	-.098***	-.437*	-.041	-.04	-.099***	-.138***	-.029	-.186***	-.133***
	(.037)	(.231)	(.199)	(.032)	(.034)	(.055)	(.063)	(.057)	(.039)
Patient Controls X Year 2022	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Doctor Fixed Effects X Year 2022	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
Date X Hour Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	62,683	17,466	13,866	62,683	62,683	29,646	29,542	29,274	30,436

This Table displays estimates of regressions of a case's log of number of tests 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 to the ED. The estimating equation is:

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

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 doctor 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), doctor and hour fixed effects, as well as patient controls (age, gender, main diagnosis and vital signs markers upon admission) interacted with the year 2022 dummy. Column 1 presents the main estimates. Columns 2 and 3 provide results cutting the sample by the the intensity in the number of test ordered by the doctor in the pre-period, columns 4 and 5 by the request frequency, columns 6 and 7 by patient age, and last 2 columns by doctor experience.

TABLE 5 - EFFECTS ON PATIENT SATISFACTION DOUBLE-DIFFERENCES MODEL

	(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

This Table displays estimates of regressions of patients' evaluations in the ED on the period during which the dashboard 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 to the ED. The estimating equation is:

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

where w indexes the ward to which the patient is assigned, t indexes the month in which the patient arrived and d indexes the doctor to which the patient was assigned. 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), doctor and month fixed effects, as well as patient controls (age, gender, main diagnosis and vital signs markers upon admission). Standard errors are clustered at the doctor level.

TABLE 6 - OTHER DEPENDENT VARIABLES
TRIPLE-DIFFERENCES MODEL

Dependent Variable =	(1) 30-Day Return	(2) Hospital Admission	(3) Total Cost	(4) Log Tests Time
Post June X Private Ward X Year 2022	.01	-.069***	-.248***	.001
	(.013)	(.014)	(.06)	(.035)
Patient Controls X Year 2022	Yes	Yes	Yes	Yes
Doctor Fixed Effects X Year 2022	Yes	Yes	Yes	Yes
Insurance Status Fixed Effects X Year 2022	Yes	Yes	Yes	Yes
Date X Hour Fixed Effects	Yes	Yes	Yes	Yes
Observations	62,683	62,683	62,576	37,586

This Table displays estimates of regressions of a case's different medical outcomes in the ED on the period during which the dashboard 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 to the ED. The estimating equation is:

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

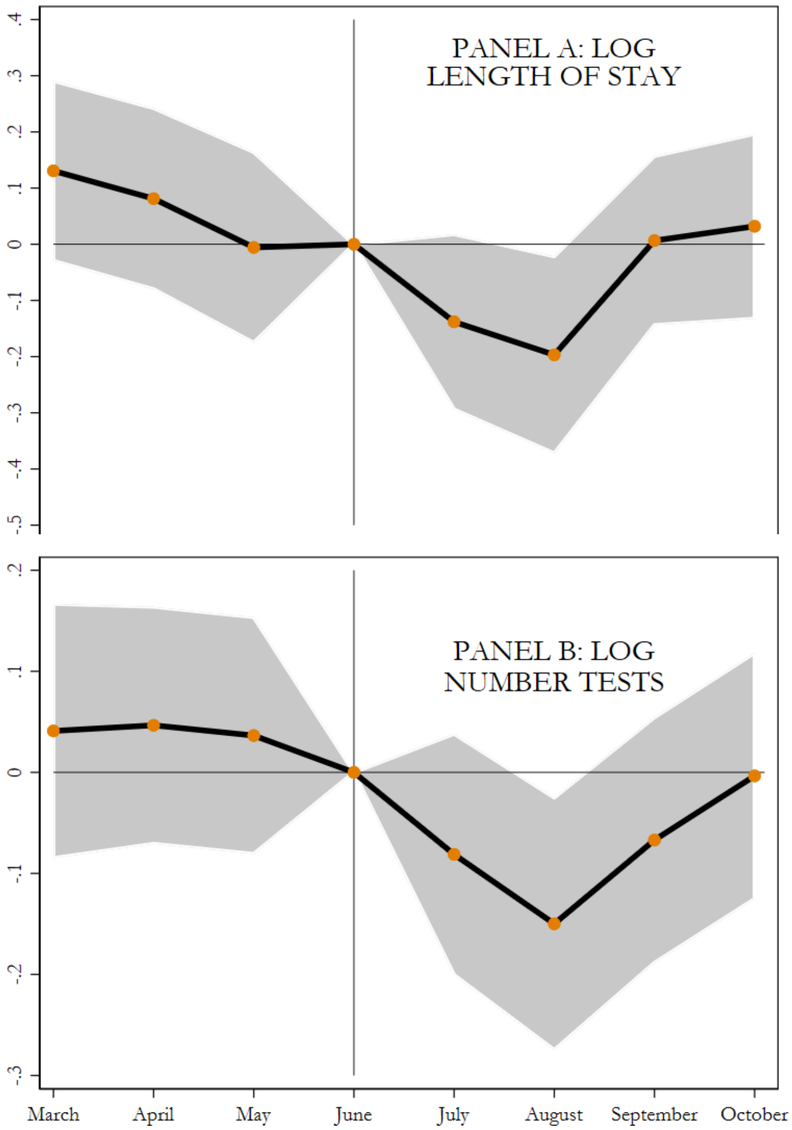
where w indexes the ward to which the patient is assigned, t indexes the exact hour (i.e. date/hour of day combination) in which the patient arrived and d indexes the doctor to which the patient was assigned. The main independent variable of interest is the interaction between being assigned to the private ward, arriving in the months between July and October, and arriving in 2022. The model controls for insurance status (which subsumes the assigned ward), doctor and hour fixed effects, as well as patient controls (age, gender, main diagnosis and vital signs markers upon admission). In Column 1, 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 Column 2, the dependent variable is a dummy if the patient is hospitalized. In column 3, we include the total cost of the episode as dependent variable. In column 4, the dependent variable is the total time that the test took to be delivered in the laboratory department. All the controls are interacted with the year 2022 dummy. Standard errors are clustered at the doctor level.

Figures

FIGURE 1: SCREENSHOT OF THE DASHBOARD DISPLAYING THE STATE OF THE LABORATORY TESTS

Orden	Nombre del Paciente	...	HEMATOLOGIA	COAGULACION	QUIMICA CLINICA	ENDOCRINOLOGIA	INMUNOLOGIA	INFECCIOSAS	LIQUIDOS CORPORALES	COPROANALISIS	REMISIONES
202107211064	CPMM CC-67000003 UE Urgencias adulto		2021-07-21 13:10		2021-07-21 13:10		2021-07-21 13:10				
202107211031	OAHG CC-29351833 UE Urgencias adulto		2021-07-21 13:12		2021-07-21 13:11	2021-07-21 13:11	2021-07-21 13:11				
202107210937	MCM CC-67007990 UE Urgencias adulto		2021-07-21 13:16		2021-07-21 13:15						
202107210877	DNM CC-29563413 UE Urgencias adulto				2021-07-21 11:50						

FIGURE 2: LEADS AND LAGS EVIDENCE (TRIPLE-DIFF)

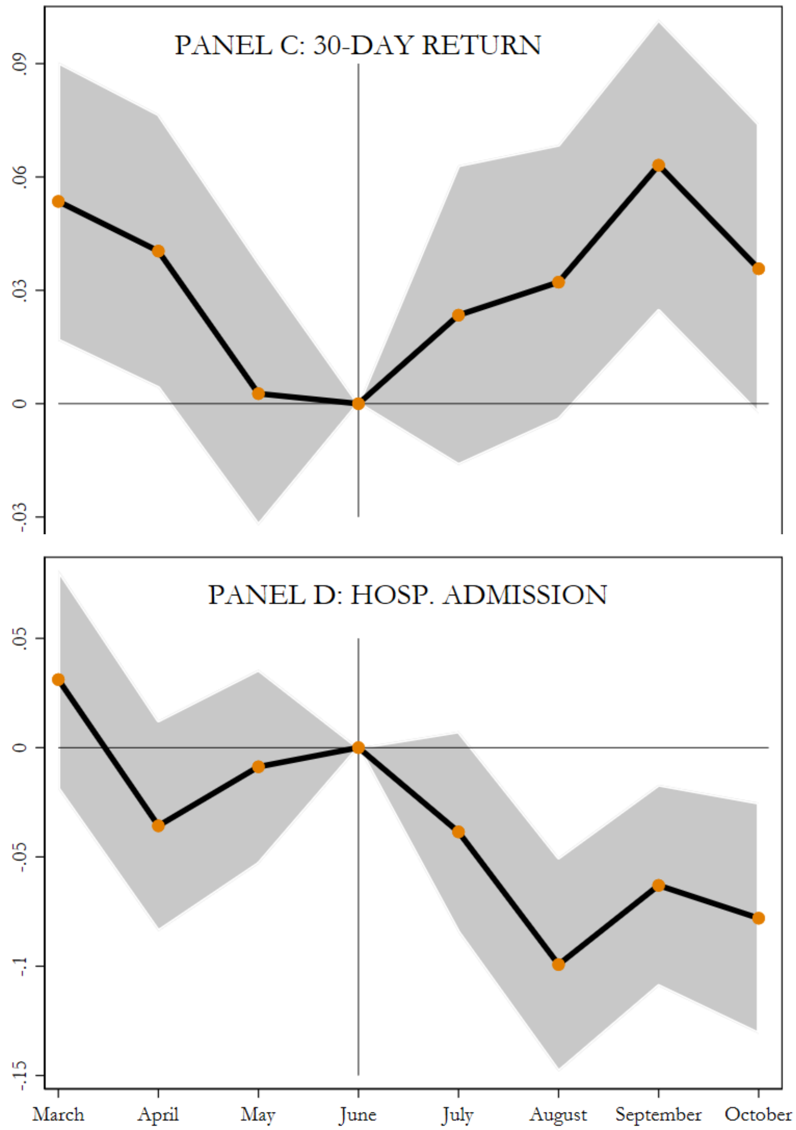


This Figure displays dynamic estimates of regressions of a case's length of stay in the ED on the period during which the dashboard was introduced, interacted with the ward in which it was introduced (i.e. prepaid ward). The unit of observation is a case i arriving to the ED. This figure displays the 8 coefficients β_j from estimating:

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

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 doctor to which the patient was assigned. The main independent variables of interest is the interaction between being assigned to the prepaid ward and each of the months before and after the introduction of the dashboard. The model controls for insurance status (which subsumes the assigned ward), doctor and hour fixed effects, as well as patient controls (age, gender and health markers upon admission). Standard errors are clustered at the doctor level.

FIGURE 3: LEADS AND LAGS EVIDENCE (TRIPLE-DIFF)

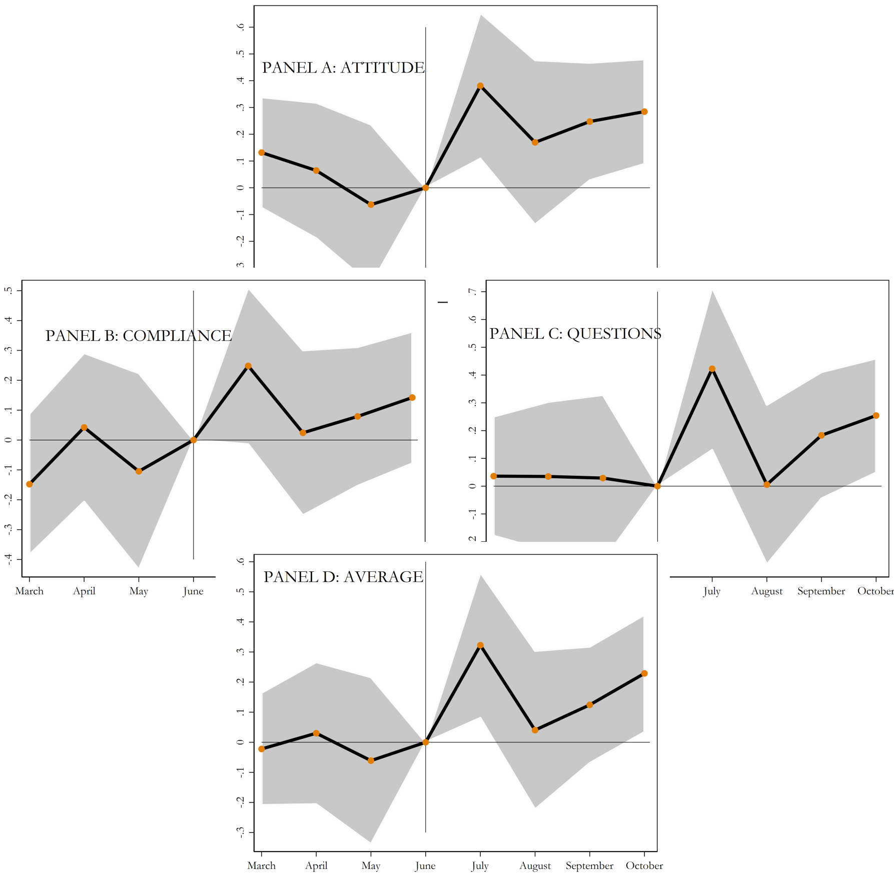


This Figure displays dynamic estimates of regressions of a case's length of stay in the ED on the period during which the dashboard was introduced, interacted with the ward in which it was introduced (i.e. prepaid ward). The unit of observation is a case i arriving to the ED. This figure displays the 8 coefficients β_j from estimating:

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

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 doctor to which the patient was assigned. The main independent variables of interest is the interaction between being assigned to the prepaid ward and each of the months before and after the introduction of the dashboard. The model controls for insurance status (which subsumes the assigned ward), doctor and hour fixed effects, as well as patient controls (age, gender and health markers upon admission). Standard errors are clustered at the doctor level.

FIGURE 5: LEADS AND LAGS EVIDENCE (DOUBLE-DIFF)



This Figure displays dynamic estimates of regressions of a case's survey evaluation on the period during which the dashboard was introduced (i.e. post 18 June), interacted with the ward in which it was introduced (i.e. prepaid ward). The unit of observation is a case i arriving to the ED. This figure displays the 8 coefficients π_t from estimating:

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

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 doctor 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 18th June. The model controls for insurance status (which subsumes the assigned ward), doctor and hour fixed effects, as well as patient controls (age, gender and health markers upon admission). Standard errors are clustered at the doctor level.

Appendix Tables and Figures

**TABLE A1 - ROBUSTNESS TO CONTROL VARIABLES
DOUBLE-DIFFERENCES MODEL**

Dependent Variable = Log Length of Stay

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Post June X Private Ward	-.517***	-.509***	-.497***	-.493***	-.567***
	(.072)	(.076)	(.074)	(.067)	(.082)
Patient Controls	No	No	No	Yes	Yes
Doctor Fixed Effects	No	No	Yes	Yes	Yes
Insurance Status Fixed Effects	No	Yes	Yes	Yes	Yes
Date X Hour Fixed Effects	No	Yes	Yes	Yes	Yes
Post June	Yes	No	No	No	No
Private Ward	Yes	No	No	No	No
Observations	29,849	29,187	29,119	29,431	23,520

This Table displays estimates of regressions of a case's length of stay in the ED on the period during which the dashboard 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 to the ED. The estimating equation in Column 4 is:

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

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 doctor to which the patient was assigned. 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), doctor and hour fixed effects, as well as patient controls (age, gender, main diagnosis and vital signs markers upon admission). In Column 1 we display the most streamlined differences-in-differences model, which only includes a post dummy and a private dummy as controls. In Column 2 we include the insurance status and the hour fixed effects (which subsume the year 2022 and private ward dummies). In Column 3 we add the doctor fixed effects. In Column 4 we add the patient controls and the top 10% of the length of stay distribution is winsorised. In Column 5 we add the patient controls and the sample includes only triage levels 1-3. Standard errors are clustered at the doctor level.

TABLE A2 - HETEROGENEITY DOUBLE-DIFFERENCES MODEL

Dependent Variable = Log Number of Tests

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Log Number Tests	Pre-Period Tests		Frequency Tests		Patient Age		Doctor Experience	
		Low	High	Low	High	Young	Old	Low	High
Post June X Private Ward	-.124***	-.412	-.065	-.064***	-.12***	-.125***	-.066	-.186***	-.133***
	(.031)	(.259)	(.207)	(.024)	(.028)	(.046)	(.052)	(.062)	(.038)
Patient Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Doctor Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Insurance Status Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date X Hour Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	29,442	1,256	1,889	29,442	29,442	13,901	13,650	6,027	21,488

This Table displays estimates of regressions of a case's number of tests in the ED on the period during which the dashboard 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 to the ED. The estimating equation is:

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

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 doctor to which the patient was assigned. The main independent variable of interest is the interaction between being assigned to the private ward and arriving in the months between July and October. The model controls for insurance status (which subsumes the assigned ward), doctor and hour fixed effects, as well as patient controls (age, gender, main diagnosis and vital signs markers upon admission). Column 1 presents the main estimates. Columns 2 and 3 provide results cutting the sample by the the intensity in the number of test ordered by the doctor in the pre-period, columns 4 and 5 by the request frequency, columns 6 and 7 by patient age (age is not included as control in these columns), and last 2 columns by doctor experience. Standard errors are clustered at the doctor level.

TABLE A3 - OTHER DEPENDENT VARIABLES DOUBLE-DIFFERENCES MODEL

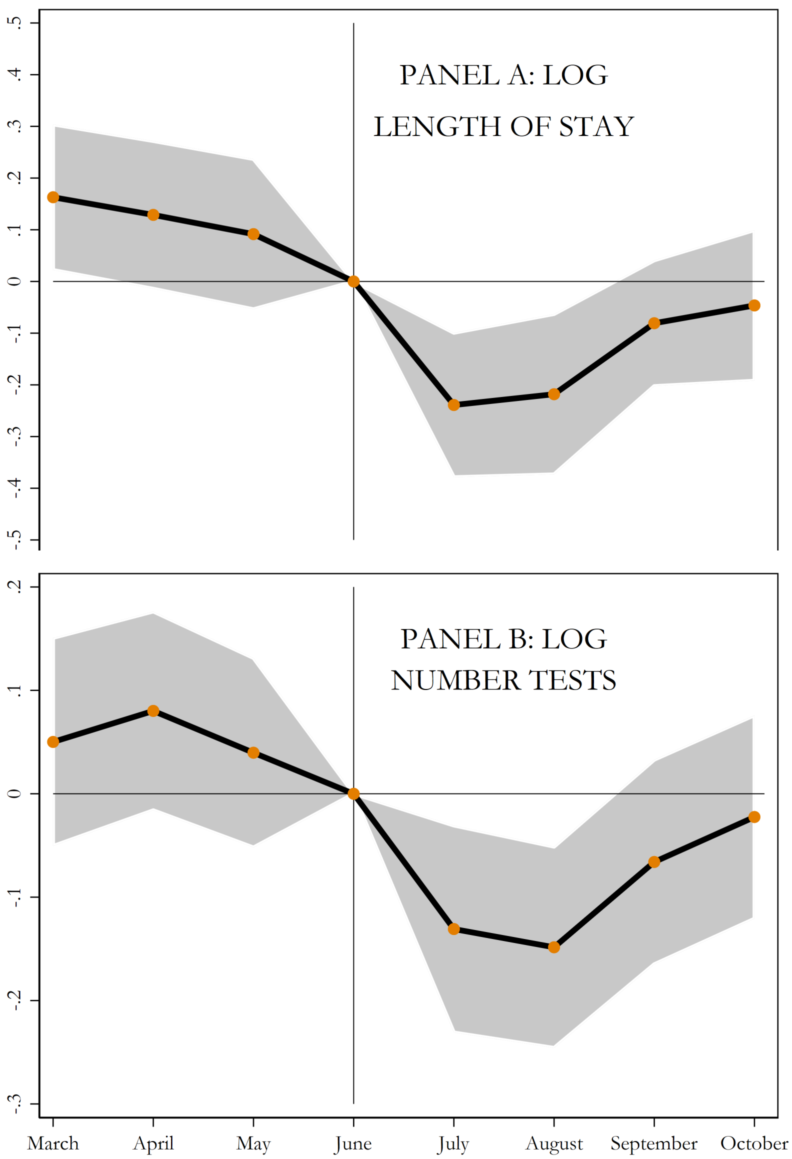
Dependent Variable =	(1) 30-Day Return	(2) Hospital Admission	(3) Total Cost	(4) Log Tests Time
Post June X Private Ward	.014	-.066***	-.26***	-.145***
	(.01)	(.012)	(.048)	(.028)
Patient Controls	Yes	Yes	Yes	Yes
Doctor Fixed Effects	Yes	Yes	Yes	Yes
Insurance Status Fixed Effects	Yes	Yes	Yes	Yes
Date X Hour Fixed Effects	Yes	Yes	Yes	Yes
Observations	29,442	29,442	29,410	18,717

This Table displays estimates of regressions of a case's different medical outcomes in the ED on the period during which the dashboard 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 to the ED. The estimating equation in Column 6 is:

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

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 doctor to which the patient was assigned. The main independent variable of interest is the interaction between being assigned to the private ward and arriving after 18th June. The model controls for insurance status (which subsumes the assigned ward), doctor and hour fixed effects, as well as patient controls (age, gender, main diagnosis and health markers upon admission). In Column 1, 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 Column 2, the dependent variable is a dummy if the patient is hospitalized. In column 3, we include the total cost of the episode as dependent variable. In column 4, the dependent variable is the total time that the test took to be delivered in the laboratory department. All the controls are interacted with the year 2022 dummy. Standard errors are clustered at the doctor level.

FIGURE A1: LEADS AND LAGS EVIDENCE (DOUBLE-DIFF)

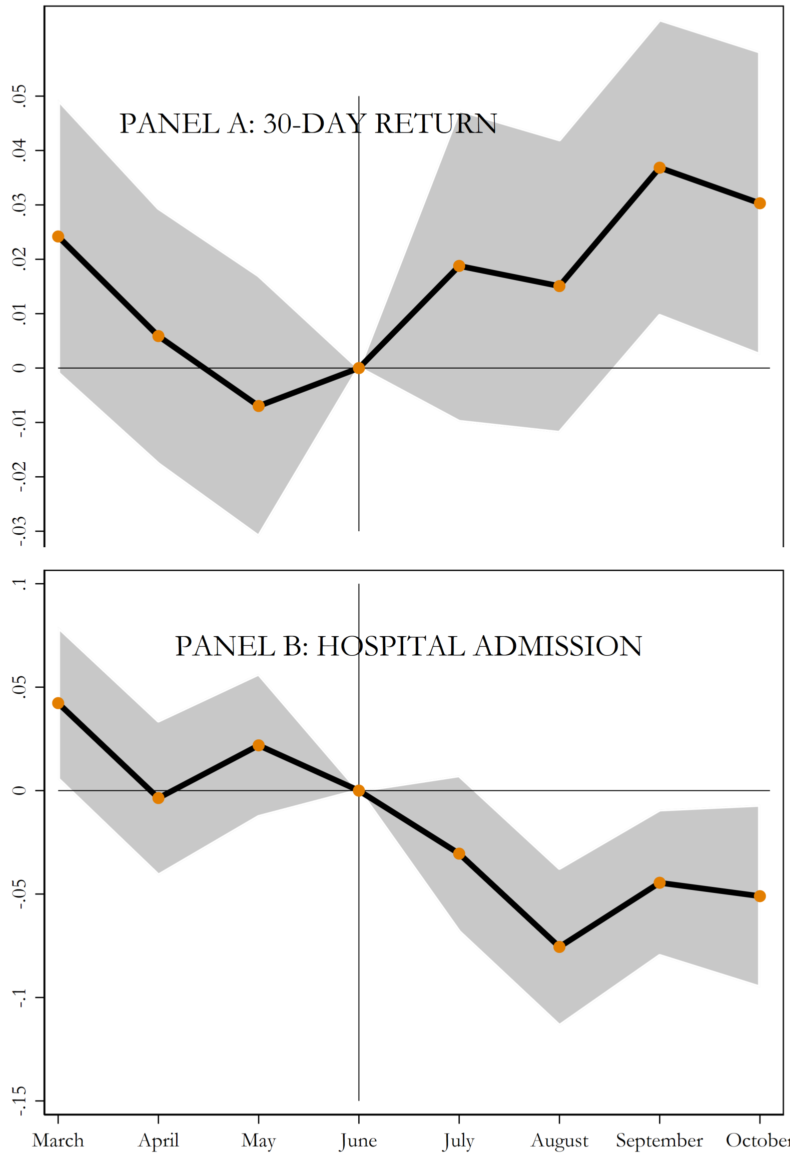


This Figure displays dynamic estimates of regressions of a case's length of stay in the ED on the period during which the dashboard was introduced (i.e. post 18 June), interacted with the ward in which it was introduced (i.e. prepaid ward). The unit of observation is a case i arriving to the ED. This figure displays the 8 coefficients β_j from estimating:

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

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 doctor 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 18th June. The model controls for insurance status (which subsumes the assigned ward), doctor and hour fixed effects, as well as patient controls (age, gender and health markers upon admission). Standard errors are clustered at the doctor level.

FIGURE A2: LEADS AND LAGS EVIDENCE (DOUBLE-DIFF)



This Figure displays dynamic estimates of regressions of a case's length of stay in the ED on the period during which the dashboard was introduced (i.e. post 18 June), interacted with the ward in which it was introduced (i.e. prepaid ward). The unit of observation is a case i arriving to the ED. This figure displays the 8 coefficients π_t from estimating:

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

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 doctor 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 18th June. The model controls for insurance status (which subsumes the assigned ward), doctor and hour fixed effects, as well as patient controls (age, gender and health markers upon admission). Standard errors are clustered at the doctor level.