Does Contact Time Matter for Patient Outcomes?

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Abstract. This paper uses a unique source of information, Real-Time Location System (RTLS) Data, to study the effect of contact time on patient health outcomes. The setting is the New Cross Hospital in Wolverhampton, England. This large district general hospital is part of the Royal Wolverhampton NHS Trust (RWT). In 2013, RWT partnered with a United States technology company to develop a real-time patient flow and tracking solution. RTLS allows us to perfectly observe the amount of time nurses spend with patients in the hospital. We exploit this data's granularity level to estimate a causal impact of contact time on patient outcomes. By decomposing contact time into an endogenous and plausibly exogenous component, we show that direct contact between nurses and patients significantly reduces in-hospital mortality and accidents.

1 Introduction

In 2023, 71% of the National Health Service (NHS) staff who have direct contact with patients said they did not have the amount of time they would like to have to help them.[1]

Although widely recognized as an essential component of good care and patient experience (Aiken et al., 2000), little is known about the relationship between contact time and patient hospital outcomes. This study aims to provide a first estimate of this relationship.

Contact time between medical staff and patients is generally considered a vital dimension of a patient stay in hospital (Barker et al., 2016; Griffiths et al., 2019). It is meant to allow the hospital staff to target, coordinate, and monitor treatment and contributes to the patient feeling cared for and supported (Aiken et al., 2000; Duffield et al., 2011; Westbrook et al., 2011). But does contact time matter for patients' outcomes?

Empirical research in this area has been challenging. Data on contact time is not widely available and difficult to collect on a large scale. Existing studies have generally relied on self-reported logs or involved an external observer recording staff movements and activities (Dall'Ora et al., 2021; Edwards et al., 2009; Hendrich et al., 2008; Yen et al., 2018b). Both approaches suffer from significant limitations and are hard to scale. Time-motion analyses require a human observer to record and characterize activities over time. This is costly, time-consuming, and captures only limited time frames and locations. Using an observer to collect this type of data may also induce individuals to change their behavior, leading to biased results (Mahtani et al., 2018). Self-reported activity logs require staff to record, without any outside interference, how they spend their time during the day (Antinaho et al., 2015). This method is subject to recall bias, as staff members often overestimate their time with patients (Donaldson and Grant-Vallone, 2002), besides being an important ask to staff who are already significantly overworked (Timmins et al., 2022).

However, data limitations have not been the only impediment to investigating the relationship between contact time and patient outcomes. Identifying a causal impact requires a plausible ex-

[1] https://www.theguardian.com/society/2023/jul/24/most-nhs-staff-say-they-dont-have-enough-time-to-spend-with-patients

ogenous variation in contact time as this may correlate with observable and unobservable patient characteristics. Hospital staff for example has been observed to spend more time with sicker patients (Despins et al., 2019), which may induce a spurious correlation between health outcomes and contact time and even suggest that more time is associated with worse outcomes. Policy experiments that have changed contact time have been difficult to come across, and to this day we are not aware of any existing study that has attempted to address this issue straight.

This paper uses a novel and unique data source, real-time location system (RTLS) data, to overcome these challenges. RTLS allows organizations to observe the movements of objects and individuals across space in real-time (Cannaby et al., 2022b). These systems have been deployed in healthcare, where they are increasingly leveraged to organize patient and staff flow (Overman, 2022). Data capture is a crucial capability of RTLS; every movement is recorded and stored in the system's memory (Cannaby et al., 2022a). RTLS data allow us to have a privileged view of the interactions between patients and nursing staff and to compute contact time accurately across an entire hospital. Having quantified the amount of contact time patients receive from nurses; we analyze whether contact time has a detectable effect on patient outcomes. We focus on three patient outcomes: mortality, transfers to the Intensive Care Unit (ICU), and accidents. These outcomes capture essential dimensions of the patient's hospital stay. Mortality is a crucial result for both the patient and the hospital. ICU transfers indicate deterioration in patients' health. Accidents are considered a marker of the quality-of-care patients receive during a hospital admission stay and the level of oversight provided.

We estimate the relationship between patient outcomes and contact time using a fixed effect Ordinary Least Squares regression to provide evidence of causal effects. Exploiting the richness of our data, we decompose the amount of contact time a patient receives into an endogenous and a likely exogenous component. We show that contact time that arises from interactions at the patient bed is endogenous as sicker patients require more care, so nurses spend more time with them at their bedside. However, we believe that a significant portion of the time nurses spend with patients is unrelated to their characteristics and can be considered unrelated to their health outcomes. In particular, we argue that the amount of time nurses spend in the patient room is uncorrelated to other determinants of patient health once we control for the patient bed-side level contact time. Under this assumption, our results suggest that contact time has a negative effect on both in-hospital mortality and accidents. An increase in contact time reduces mortality by 0.03% and accidents by 0.01%. This is evidence of the importance of direct care in hospitals for patient outcomes.

This paper contributes to two strands of literature. First, an extensive literature in health services that measures contact time as an end in itself. Among all, Butler et al. (2018) has the approach closest to us. They use a sensor-based measurement of contact time within an intensive care unit and show that nurses spend 32% of their time with patients. Other studies use less sophisticated contact measurements; for example, direct observation of nurses taking vital signs suggests that this is a time-consuming process (Dall'Ora et al., 2021). This type of observation also suggests that hands-on tasks of nurses occur during the day and that a plurality of time is spent within the nursing station and charting (Yen et al., 2018a). This relates directly to concerns within medicine on the over-proliferation of non-clinical work. Surveys suggest that physicians find the amount of time devoted to paperwork and administrative tasks has increased to the detriment of clinical work (Government of Nova Scotia, 2020). The introduction of electronic health records has been associated with an increase in time spent on documentation by 8% among consultant physicians (Joukes et al., 2018) and nearly 45% increase in documentation tasks within the ICU (Carayon et al., 2015). Surgical residents spend nearly 24 hours on documentation during a week (Cook et al., 2010). Overall, the impact of introducing electronic health records seems to increase the overall documentation time (Baumann et al., 2018)which is in line with survey responses that suggest an increase in documentation in lieu of face-to-face contact time. This increase in documentation is associated with physician burnout (OMA, 2021). Our contribution to this literature is to show that direct contact with patients matters. Trends towards additional administrative tasks will likely result in poorer patient outcomes.

This links to a second piece of literature on nurse staffing. Much of the current theory on nurse staffing levels and patient outcomes relates to better oversight. More nurses mean more oversight due to more direct observation of patients (Shekelle, 2013). There has been mixed evidence that additional nurse staffing improves outcomes. Most associations between patient outcomes and staffing levels show improvements in patient outcomes with higher staffing levels (Aiken et al., 2000; Griffiths et al., 2019; Haegdorens et al., 2019; Musy et al., 2021; Needleman et al., 2011;

Zaranko et al., 2022). Policy experiments have been more challenging to find. A notable exception has been the adoption of minimum nursing ratios in Australia, which was associated with 7% reductions in mortality and readmissions (McHugh et al., 2021). Similar mandates in California have demonstrated mixed evidence; while surveys of nurses report better quality of care (Aiken et al., 2010), administrative data suggests no improvement in patient outcomes like mortality despite the policy improving staffing ratios (Cook et al., 2010). We provide a plausible mechanism underpinning this literature: direct contact time improves patient outcomes.

This paper proceeds as follows. In Section 2 we describe the RTLS system, our measure of contact time, and the data on patient outcomes. In Section **??** we present our empirical strategy and results. Finally, Section 4 concludes.

2 Data

The setting of this paper is the New Cross Hospital in Wolverhampton, England. This is a large district general hospital part of the Royal Wolverhampton NHS Trust (RWT). The Trust is one of the main healthcare providers in the West Midlands, covering acute, community, and primary care services.

In 2013, RWT partnered with a United States technology company to develop a real-time patient flow and tracking solution (Nash, 2014). This application was intended to support staff in delivering care and to enhance efficiency through the process of providing real-time operational information across clinical areas. The RTLS requires four main components:

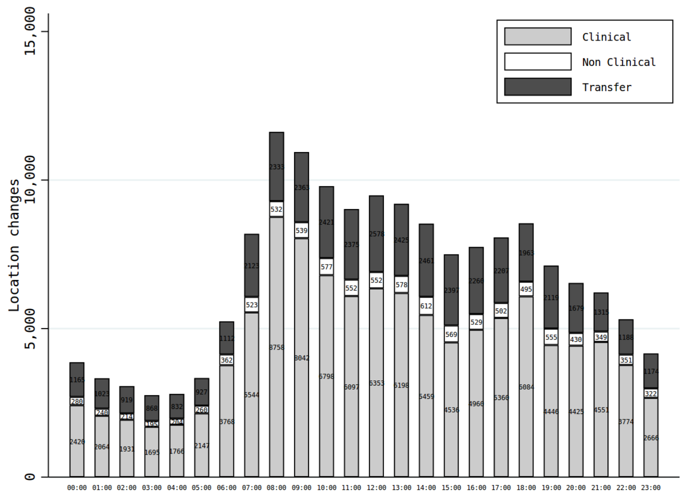
- A locating node (i.e., multiple boxes on the ceiling covering clinical areas),
- A location server (the computer that receives all the data),
- A user application (the software that interprets the data),
- The tag (typically a badge worn by members of staff, patients, and equipment)

RTLS tags can be worn by staff – on a lanyard or clip – while patients have it attached to a wrist or ankle via a bracelet. The technology transmits continuous location data that is unique to the

Figure 1: RTLS components

Note: The figure shows the locating node and the badges worn by staff and patients.

Figure 2: Tracking movements in a day



Note: Total location changes by hour and location type. Source RTLS data at RWT.

tagged person or item in real or near-real-time (Kamel Boulos and Berry, 2012).

The RTLS at RWT provides real-time tracking of all staff and patients across 564,916 square feet of the New Cross hospital site. As of April 2022, RWT has issued 7218 staff badges, and all patients are badged on admission for their stay within the hospital (Cannaby et al., 2022b). We show the privileged view that the RTLS buys us into the workings of the hospital in Figure 2. Each observation in our data is a location change; someone going in and out of a location. We classify hospital areas into clinical (e.g., bays), non-clinical (e.g., waiting rooms), and transfer (e.g., corridors, halls) and track how many location changes we observe in each of these over the course of a day. Clinical areas are the places where most movements occur. Between 8 and 9 AM on average, we can observe more than 8500 staff movements in and out of locations.

2.1 Patients' contact time with nursing staff

We utilize RTLS data from April 2016 to April 2019 to measure how much contact time patients receive from nursing staff, including registered nurses and health care support workers (RNs and HCSWs).

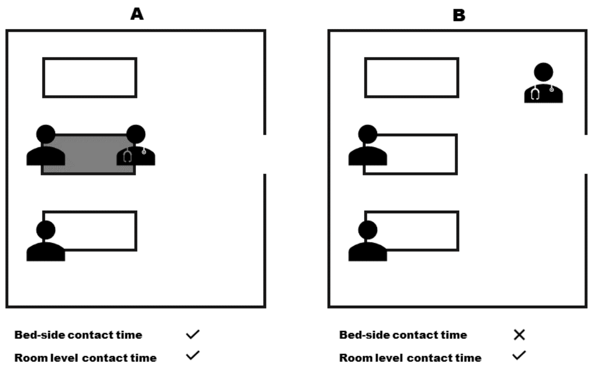
The starting point is to identify time lapses when the patient and the nurse interact at a given location. We focus on two types of interactions: those at the patient's bed and those in the patient's room.[2] Our sample comprises more than 20 million interactions between patients and nursing staff.

We compute bed-side contact time as the total number of minutes a patient spends with staff at the location identified as the patient's own bed. We define room-level contact time as time spent by nurses and patients together in the room where the patient's bed is located, regardless of whether the interaction is detected at the patient's bed side. Figure 3 presents two scenarios illustrating the difference between bed-side and room-level contact time. In Scenario A, the nurse is at the bed-side of Patient 1 (in gray); this interaction will feed into Patient 1 bed-side contact time but will also account for both patients' room-level contact time. The interaction in Scenario B will account for both patients' room-level contact time but contribute to neither bed-side level contact time. Contact time is then computed as the total number of minutes nurses spend with patients at their bed (bed-side contact time) or in the patient's room (room-level contact time).

Figure 4 presents the bed-side and room-level contact time distribution. An observation in our data corresponds to a unique patient-day combination. The top and bottom sides of the box are the lower and upper quartiles. The box covers the interquartile interval, where 50% of the data is found. The horizontal dotted line in gray that splits the box in two is the median, and the horizontal dotted line in blue indicates the mean. The median bed-side contact time is 16 minutes, while the mean is 22. The median room-level contact time is 7 hours, while the mean is 8. Both distributions display significant heterogeneity, with different patients receiving significantly different amounts

[2] We don't have data on the assignment of patients to beds or rooms, but we can reliably identify assignments using the RTLS data itself. We compute the number of hours we observe each patient in hospital on a given day. The system tracks the average patient in our sample for 15 hours daily. The patient's bed is identified as the bed location where the patient spends most of his/her day. For most of the patients in our data, the assigned bed accounts for 90 percent of the time they are observed in the hospital indicating that our imputation method is reasonable. To further check the accuracy of the imputation, we examine whether the patient diagnosis codes are consistent with the location of his/her bed. This check substantiates that we can reliably identify the location of the patient's own bed.

Figure 3: Bed-side and Room-level Contact Time



Note: Panel A shows what accounts for bed-side level contact time. Panel B shows what accounts for room-level contact time. All bed-side contact time accounts as room-level contact time

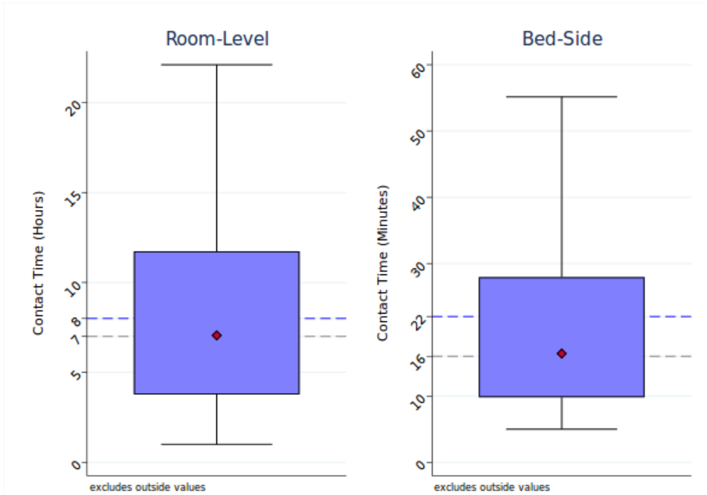
of contact time. Bed-side contact time is also concentrated on particular moments of the day, as seen in Figure 4. The most significant amount of bed-side contact time is between 8 and 12 AM. This aligns with previous findings documenting that nurses' work is not distributed equally across a 12-hour shift and that hands-on tasks mainly occur between 7 and 11 AM (Yen et al., 2018b).

2.2 Complementary Data

We complement the RTLS data with information on patient characteristics from the hospital's inpatient episode dataset. This includes patient clinical and demographic information. From this data, we identify the date of the patient's death. Further, we use data from the incident reporting system data at RWT, which collects all reported adverse events involving patients, staff, and visitors at the hospital. We observe the time and the day when these incidents occur, the location, whether the adverse event has caused any harm to the patient, and the type of event (e.g., pressure ulcer, wrong medication). Finally, we monitor deterioration in a condition necessitating higher levels of care with any transfer to the intensive care unit at RWT, which we detect using RTLS data.

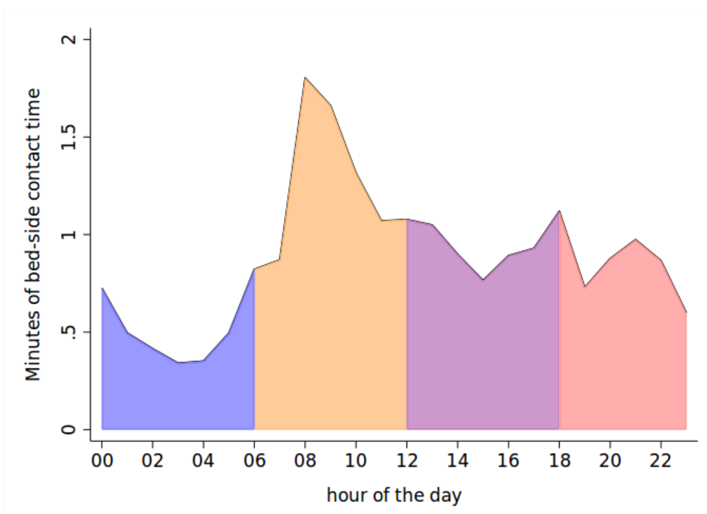
Our sample of patients includes all individuals admitted for inpatient care to the hospital during the observation period across 20 inpatient wards. 60 percent of patients are males, 78 percent are white, and the average patient is 64 years old and has a length of stay of 20 days. 0.3 percent of

Figure 4: Distribution of Contact Time



Note: Scatter plot of bed-side and room-level contact time. Does not include outside values. Bed-side contact time is minutes per day and patient. Room-level contact time is in hours per day and patient.

Figure 5: Minutes of Bed-Side Contact Time by the Hour (**Patients**)



Note: Average number of minutes per hour patients and nurses are observed together at the patient's bed.

patients experience death in the hospital, 1.2 experience an accident, and 0.09 are observed being transferred to the ICU during their hospital stay.

Our sample of staff from the RTLS includes all RNs and HCSWs employed by the hospital between 2016 and 2019. RNs are qualified nurses who coordinate access and deliver prescribed care to patients. RNs have either a foundation or bachelor's degree in nursing and are registered practitioners with the Nursing/Midwifery Council (NMC). HCSWs work under the guidance of a healthcare professional, such as a nurse or a doctor. In a hospital setting, they may assist with the patient's hygiene needs and help mobilize and monitor patients' conditions. For part of the nurses in our sample, we can identify their gender, nationality, and experience in the NHS. For this subset, we can observe that 75 percent are female, 81 percent are British, and the average nurse has ten years of experience.

Table 1: Patients Summary Statistics

	mean	sd	min	max
Share Female	0.39	0	0	1
Share White	0.78	0	0	1
Age	64.5	16	15	90
Charlson Index	2.3	2	0	15
Length of Stay	19.5	25	0	583
Daily Bed-Side Contact Time (Minutes)	22.3	19.2	5	593.8
Daily Room-Level Contact Time (Hours)	8.2	5.3	1	22.1
Mortality	0.003	0	0	1
Accidents	0.012	0	0	1
ICU Transfers	0.009	0	0	1
Observations	66825			

* Note: Source RWT inpatient records, 2016/2019.

Table 2: Nurses Summary Statistics

	mean	sd	min	max
Panel A				
Share of Registered Nurses	0.64	0	0	1.0
Days Worked Monthly	13.63	5	1	31.0
Observations	203601			
Panel B				
Share Female	0.75	0	0	1.0
Share British	0.81	0	0	1.0
Years of Experience	10.18	9	0	52.0
Observations	63989			

* Note: Source RWT RTLS data and HR records, 2016/2019.

3 Empirical Strategy

Our empirical strategy is tailored to identifying causal effects in the presence of endogeneity, which arises because the amount of contact time a patient receives is likely a function of their characteristics and, hence, their outcomes. Omitted health variables, in particular, are a concern in this context. For example, nurses may spend more time with patients whose condition is deteriorating rapidly. The nurses can observe this health measure, but the econometricians can't. This in turn could bias any estimate such that we might expect a much reduced or even negative relationship between contact time and outcomes.

An ideal experiment to address this concern would be a randomized control trial (RCT) where we could exogenously change the amount of contact time each patient receives. Within an RCT, averaging differences in outcomes between the control and treatment groups would be sufficient to identify a causal effect of contact time.

We do not observe any exogenous change in contact time which would be appropriate to approximate this setting. However, we believe the granularity of our data allows us to distinguish between the contact time patients receive because of their health status and the contact time patients receive because of other reasons unrelated to their health. We lay out our identification strategy below.

3.1 Identification Argument

Assume that the following relationships can express the true model of contact time and patient outcomes:

$$Y_{irt} = \beta_0 + \beta_1 CT_{irt} + \beta_2 X_{irt} + \beta_3 H_{irt} + \epsilon_{irt} \tag{1}$$

$$CT_{irt} = f(X_{irt}, H_{irt}) \tag{2}$$

Where Y_{irt} is a binary indicator of whether a patient i residing in room r has experienced negative health outcome on day t (i.e., death, ICU transfer, or accident) and CT_{irt} is the amount of contact time patient i receives on day t. X_{irt} and H_{irt} represent respectively all observed and unobserved factors affecting the outcome and the amount of contact time the patient receives (e.g., age, vital signs). Lastly, ϵ_{irt} and u_{irt} represent an idiosyncratic component.

As we can at best only observe X_{irt}, the model we can plausibly bring to the data would be:

$$Y_{irt} = \alpha + \beta_1 CT_{irt} + \beta_2 X_{irt} + \eta_{irt} \tag{3}$$

$$\eta_{irt} = \beta_3 H_{irt} + \epsilon_{irt} \tag{4}$$

Estimating β_1 in this case would lead to a biased result because of our inability to observe H_{irt}. To attenuate this problem and provide evidence on the causal relationship between contact time and patient outcomes, we make a simple distinction between what we call bed-side and room-level contact time.

We argue that bed-side level contact time is endogenous as sicker patients require more direct care and, for this reason, are given more contact time by nurses. However, we assume that the amount of time nurses spend in the patient room is likely unrelated to any unobserved determinants of health once we control for the amount bed-side contact time patient i receives on day t. In particular, we assume contact time is the result of the following relationships:

$$CT_{irt} = CT_{irt}^{B} + CT_{irt}^{R} \tag{5}$$

$$CT_{irt}^{B} = h(X_{irt}, H_{irt}) \tag{6}$$

$$CT_{irt}^{R} = \Sigma_{j \neq i}^{N_r} g_j(CT_{jrt}^{B}) + g_i(CT_{irt}^{B}) \tag{7}$$

In this model, the amount of contact time patient i receives is given by the sum of CT_{irt}^{B}, the bed-side level contact time, and CT_{irt}^{R} the room-level contact time received by patient i on day t. CT_{irt}^{B} is a function of both observed and unobserved factors affecting the outcome and, in this sense, endogenous. CT_{irt}^{R} is a function of the bed-side contact time of the patients in room r and patient i contact time. The bed-side contact time of the patients in room r is unrelated to patient i characteristics and hence, once we control for CT_{irt}^{B} room-level contact time is unrelated to any unobserved determinant of health.

3.2 Estimation

In practice, we estimate the following model:

$$Y_{irt} = \alpha + \beta^B CT^B_{irt} + \beta^R CT^R_{irt} + \gamma N_{rt} + \delta X_{irt} + W_{rt} + \epsilon_{irt} \tag{8}$$

Y_{irt} is a binary indicator of whether a patient i residing in room r has experienced negative health outcomes on day t (i.e., death, ICU transfer, or accident). CT^B_{irt} is the bed-side level contact time received by patient i on day t. CT^R_{irt} is the room-level contact time received by patient i on day t. N_{rt} is the number of patients in room r on day t. W_{rt} represents the interaction between the ward where room r is located and the day t. X_{irt} includes patient i clinical information (e.g., age, comorbidities) and the characteristics of the average patient in room r , as well as an additional proxy of health status which is the distance between the patient bed and the nursing station. We cluster standard errors at the ward level.

4 Results

In Table 3 we show the results from estimating the model in Equation 8 where the dependent variable is a binary indicator of the patient death on day t.

In column (1) we control for ten comorbidity indicators, primary diagnosis code, age, age squared, the average characteristics of the patients in the room, the distance between the patient bed and the nursing stations, and the interaction between ward and day. The coefficient on room-level contact time is negative and statistically significant, indicating that an increase in contact time is associated with a diminished probability of death. In column (2) we control for bed-side contact time. The coefficient on room-level contact time becomes more negative. Adding the number of patients in the room as an additional control in column (3) does not change the result.

The estimates suggest that one minute more of contact time is associated with a -0.000635 percentage point change in the probability of death, or a one-unit increase in contact time reduces in-hospital mortality by 0.3%. This reduction is not negligible, as it suggests that for ten more minutes of additional contact, patient mortality would drop by almost 3%. Assuming that for a 12-hour shift 40 percent of the time is spent in direct contact with patients, adding one more nurse to a ward with ten patients would result in a drop in mortality of 8.64 percent. This result is in line with Zaranko et al. (2023) where the authors show that on average, an extra 12-hour shift by an RN was associated with a reduction in the odds of a patient death of 9.6%.

Table 3: OLS regression - Dependent variable binary indicator of patient death

	(1)	(2)	(3)
Room-level CT	-0.00000332***	-0.00000635***	-0.00000635***
	(0.000000690)	(0.00000116)	(0.00000114)
Bed-side CT		0.000114***	0.000112***
		(0.0000200)	(0.0000197)
Room patients (N)			0.000669**
			(0.000206)
Share of deaths	0.002	0.002	0.002
Room-level CT (mean)	439.154	439.154	439.154
Bed-side CT (mean)	16.572	16.572	16.572
N	227395	223996	227395

Standard errors in parentheses are clustered at the ward level
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In Table 4 we show the results from estimating the model in Equation 8 where the dependent variable is a binary indicator of the patient being transferred to ICU on day t. The estimates are negative but not statistically significant, and we cannot exclude a zero effect for this outcome.

Table 4: OLS regression - Dependent variable binary indicator of patient ICU transfer

	(1)	(2)	(3)
Room-level CT	-0.00000340	-0.00000350	-0.00000356
	(0.00000315)	(0.00000260)	(0.00000261)
Bed-side CT		0.00000124	0.00000278
		(0.0000252)	(0.0000237)
Room patients (N)			0.000579
			(0.000283)
Share of icu transfers	0.004	0.004	0.004
Room-level CT (mean)	439.154	439.154	439.154
Bed-side CT (mean)	16.572	16.572	16.572
N	227395	223996	227395

Standard errors in parentheses are clustered at the ward level
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In Table 5 we show the results from estimating the model in Equation 8 where the dependent variable is a binary indicator of the patient experiencing an accident on day t. The coefficient on room-level contact time becomes is negative and statistically significant. Also, in this case, adding the number of patients controlling for bed-side level contact time makes the coefficient more negative. The estimates suggest that a one-unit increase in contact time reduces the probability of the patient experiencing an accident by 0.1%.

Table 5: OLS regression - Dependent variable binary indicator of patient accident

	(1)	(2)	(3)
Room-level CT	-0.00000329**	-0.0000120***	-0.0000119***
	(0.00000108)	(0.00000111)	(0.00000109)
Bed-side CT		0.000334***	0.000329***
		(0.0000207)	(0.0000201)
Room patients (N)			0.000460
			(0.000261)
Share of Accidents	0.013	0.013	0.013
Room-level CT (mean)	439.154	439.154	439.154
Bed-side CT (mean)	16.572	16.572	16.572
N	227395	223996	227395

Standard errors in parentheses are clustered at the ward level
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5 Conclusive Remarks

Using novel data from RTLS we showed that contact time between patients and nurses significantly affects the health outcomes of patients in the hospital. The estimates suggest that one minute more of contact time is associated with a -0.000635 percentage point change in the probability of death, or a one-unit increase in contact time reduces in-hospital mortality by 0.3% and accidents by 0.1%. These results are achieved under a critical assumption: once we control for bed-side contact time, room-level contact time is not correlated to unobservable patient health characteristics. Further work is needed to provide more evidence on the validity of this assumption. However, we believe this paper is an important step in delivering substantive evidence that contact time matter for patient outcomes.

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