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Can targeting high-risk patients reduce readmission rates? Evidence from Israel

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ABSTRACT

We study a large intervention intended to reduce hospital readmission rates in Israel. Since 2012, readmission risk was calculated for patients aged 65 and older, and high-risk patients were flagged to providers upon admission and after discharge. Analyzing 171,541 admissions during 2009–2016, we find that the intervention reduced 30-day readmission rates by 5.9% among patients aged 65–70 relative to patients aged 60–64, who were not targeted by the intervention and for whom no risk-scores were calculated. The largest reduction, 12.3%, was among high-risk patients, though some of it may reflect substitution of attention away from patients with unknown high-risk at the point of care. Post-discharge follow-up encounters were significantly expedited. Estimated effects declined after incentives to reduce readmission rates were discontinued. The evidence demonstrates that informing providers about patient risk in real-time coupled with incentives to reduce readmissions can improve care continuity and reduce hospital readmissions.

1. Introduction

Reducing readmissions, defined as unplanned rehospitalizations within 30 days of an initial hospitalization (Leppin et al., 2014), has long been recognized as an important quality improvement target. In the United States, the Hospital Readmissions Reduction Program (HRRP) has imposed penalties on hospitals based on their performance on readmissions since 2012 (so far, penalties have surpassed 1.3 USD billion), and in the United Kingdom, readmissions have not been separately reimbursed since 2011 (Kristensen, Bech, & Quentin, 2015). These incentives intensified providers' efforts to reduce hospital readmissions (Mellor, Daly, & Smith, 2017). Readmission reduction interventions increasingly incorporate risk prediction algorithms to prioritize high-risk individuals (Burke & Coleman, 2013; Kripalani, Theobald, Anctil, & Vasilevskis, 2014;

Zhou, Della, Roberts, Goh, & Dhaliwal, 2016). Nonetheless, there is limited evidence regarding the effectiveness of prioritizing patients based on predictive modeling.

To address this gap, we examine the effectiveness of an organization-wide intervention to reduce readmission rates that was initiated in 2012 by Clalit Health Services (henceforth Clalit), Israel's largest integrated care delivery organization. To target high-risk patients, this intervention utilizes a preadmission readmission prediction score based on a pretrained model (Shadmi et al., 2015). The score was routinely calculated for all 1.5 million Clalit members over 65 years old and communicated both to hospital providers upon admission and to primary care providers after discharge, with the aim of shifting their attention toward patients at high risk of being readmitted. The intervention was initiated following a program by the Israeli Ministry of Health that offered financial incentives to Israeli healthcare organizations that reduced readmission rates. Although the Ministry of Health incentive program was discontinued in 2014, 2 years after its start, the intervention by Clalit continued thereafter, allowing us to evaluate the role of financial incentives in facilitating the success of this intervention.

While existing work studies the impact of financial incentives and quality interventions on readmission reduction in other contexts (Nuckols et al., 2017), the intervention we study stands out in two important ways. First, it is based on predictive modeling of risk, using a publicly available, peer-reviewed, and validated risk model. Second, its scope is several orders of magnitude larger than the average existing studies (cf., Nuckols et al., 2017, where the average intervention only covers a few hundred cases). This study therefore provides new evidence on specific channels that facilitate readmission reduction on a large scale.

To identify the impact of this intervention, we use a difference-in-differences (DD) approach, exploiting the sharp 65-years-old age cutoff used to target patients for the intervention. Specifically, we compare patient readmission rates and other outcomes before and after the intervention was initiated, and between patients aged 65–70 (who were targeted by the intervention and therefore had risk scores) and a comparison group of patients aged 60–64 (who were not targeted and therefore had no risk scores). We use administrative data from Clalit on all 171,541 admissions of 60–70 year-old patients to internal medicine units at any Israeli hospital during 2009–2016. Rich clinical and electronic health records (EHR) on the history of each patient allow us to separately study the impacts on patients with readmission risk in the top 15% (the internal definition for "high-risk patients"), by retrospectively calculating the risk scores of patients aged 60–64 and using a triple-difference design (DDD).

Within the first 2 years after the intervention was initiated (2012–2014), readmission rates among the 65–70 year-old patients declined by 5.9% from their 2009–2011 average rate of 16.9% (a decline of one percentage point), both in absolute levels and in comparison with the readmission rates of patients aged 60–64 years old, which did not decline after 2012. These results are robust to accounting flexibly for time trends, hospital fixed effects, and controlling for other characteristics. The decline in readmission rates was particularly large among high-risk patients, whose readmission rates declined by 12.3% from their 2009–2011 rate of 33.3% (a decline of 4.1 percentage points), although we cannot rule out the possibility that some of the estimated effects of the intervention reflect a shift of attention from patients 60–64 years old toward the targeted older

patients. The DDD estimates are similar to the DD estimates, suggesting that the latter are not driven by differential time trends.

Further evidence suggests that the reduction in readmission rates was facilitated by improved primary care follow-up post-discharge. We find that whereas before the intervention, patients aged 65–70 had similar probability and timing of post-discharge primary care encounters as the patients aged 60–64, after the intervention (which included notifying primary care providers of their discharged patients' risk scores), the patients aged 65–70 had a significantly higher chance of having a primary care encounter within 30 days after discharge.

One potential concern when evaluating the impact of incentive programs to reduce readmission rates is that a reduction in 30-day readmission rates may mask attempts by stakeholders to hit policy targets by, for example, inefficiently extending the length of the index admission, deferring readmissions to just beyond the 30-day mark (Gupta, 2017), or selectively admitting or readmitting patients to certain hospitals (Alexander, 2017). We show evidence suggesting that this was not the case in Israel. The length of stay during the index admission and the total cost of the index admission remained unchanged, the decline was in readmission rates to any hospital (not just the one responsible for the index admission), the intervention was associated with a decline not only in 30-day readmission rates (the incentive-program target measure), but also in 60- and 90-day readmission rates, and the intervention was associated with a modest decline in subsequent one-year all-cause mortality. However, the timing of the effect does appear to respond to the financial incentives by the Ministry of Health. The magnitude of both the reduction in readmission rates and the expedited timing of post-discharge primary care encounters for the targeted population peaked during the first 2 years of the intervention, while the Ministry of Health incentives were in place. They subsequently declined, after these incentives were discontinued.

Taken together, the results suggest that communicating risk scores to hospital and primary care providers can help focus organizational efforts to reduce readmissions in high-risk populations, either by increasing overall attention to patients with high readmission risk or by shifting providers' attention from one group of patients to another. Overall, it suggests that not all readmissions are "forces of nature," and that the combination of appropriate risk modeling and staffing decisions could generate nontrivial reductions in readmission rates. Finally, the decline in the estimated effects over time suggests that maintaining such efforts should be incorporated within general organizational and incentive strategies for sustained impact.

The rest of this paper is organized as follows. Section 2 discusses the institutional background. Sections 3 and 4 describe the data and empirical strategy. Section 5 discusses the results. Section 6 presents additional analysis of the heterogeneity of the effects across several dimensions. Section 7 concludes.

2. Institutional background

The readmission reduction program we study was implemented in Clalit Health Services, one of the four non-for-profit integrated healthcare financing and delivery organizations in Israel, which covers over four million members (about 54% of the market). Clalit's

patients are admitted to all of Israel's 28 general hospitals, eight of which it directly owns and operates. It also operates 1,400 primary clinics across the country.

The readmission reduction program was initiated in response to a national incentive scheme to reduce hospital readmission rates initiated by the Israeli Ministry of Health. The program included the distribution of bonus payments to health funds reaching a 10% annual reduction of readmission rates in 2012 and a 20% reduction of readmission rates in 2013, relative to their 2010 baseline rate. In addition to incentive payments for readmission reduction, which accounted for 90% of the program's annual budget, 10% of the annual budget was allocated to support standard reporting of the time between discharge and post-discharge primary care encounters, with the aim of expediting such encounters, which are believed to facilitate the continuity of care. For the purpose of calculating eligibility for payments, an index admission was defined as any admission of a patient of any age to any hospital in Israel that lasted two or more nights and ended with a discharge from an internal medicine ward; a readmission was defined as an admission with an overnight stay of the same patient to any ward in any Israeli hospital within 30 days. The Ministry of Health announced the program in December 2011.[1] It was in effect in 2012–2013 and discontinued afterwards.

To address the ambitious goals of the Israeli Ministry of Health's program, in 2012, Clalit developed and deployed an intervention for reducing readmission rates among its covered patients. The intervention had three components. First, a unified high-risk case identification strategy was developed based on the PREADM model. This model uses clinical and utilization data from before the admission to predict readmission probabilities upon the second day of hospitalization in internal medicine units of general hospitals (the development and validation of this model are discussed in Shadmi et al., 2015). As we show below, high-risk admissions involve a large share of patients with multiple comorbidities, who face more complex coordination challenges, and who may find it more difficult to visit primary care clinics, fill their prescriptions, or adhere to instructed treatments, which may result in patient readmission. To prevent such situations, the intervention's rationale was to prioritize and improve contact with these cases at multiple critical junctions. PREADM scores were incorporated in the EHR systems of all relevant stakeholders, including all of Clalit hospitals' EHRs and all Clalit's primary care clinics. Since mid-2012, PREADM risk scores were calculated at the beginning of every month for all covered beneficiaries, so that when a beneficiary is admitted to a hospital, a score is readily available. The model was trained once, using a 2010 sample of admissions. The same coefficients were used throughout the intervention period and are still in use as of 2018 (Clalit continued the intervention even after the discontinuation of the incentive program by the Ministry of Health in 2014). Although the incentives by the Ministry of Health applied to patients of all ages, scores were only calculated for patients aged 65 and older (in the beginning of the month of the index admission), under the assumption that younger patients typically face lower readmission risk. We exploit this age cutoff in our subsequent analysis.

The second part of the intervention, which started in mid-2012, introduced a new role of care transition nurses (CTNs). CTNs were instructed to review the list of the PREADM

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[1]The incentive program budget was approved by the parliament as part of the 2012 budget. A total annual budget of 40 million NIS was allocated to the incentive program to reduce readmission rates. Clalit's total hospital budget was 8 billion NIS, and it was running an annual deficit of 500 million NIS at the time.

scores and devote particular attention to patients at the highest risk for readmission.[2] Although no formal cutoff was provided, stakeholder discussions (performed annually with CTNs and deputy medical and nursing directors of the hospitals) formed a consensus definition for high-risk patients as a risk score of 50 or more (the range was 0–100), corresponding to the 15% of cases with the highest readmission risk (with average readmission rates of 33%). Additionally, physicians and nurses in the internal medicine units were guided to utilize the PREADM score to identify the highest-risk patients and to directly deliver discharge planning to them and/or to involve the CTN if the CTN had not already identified the patient. Because Clalit patients can be admitted to any hospital in Israel – not just to hospitals owned by Clalit – special EHR systems were incorporated to communicate PREADM scores and CTN nurses were assigned in all general hospitals, both Clalit- and non-Clalit-owned.

The third part of the intervention included communicating PREADM scores, via push notifications, to primary care clinics of discharged patients. These clinics were instructed to contact high-risk patients for follow up within 48 hours of discharge. Structured follow-up by the primary care clinics' staffs (physicians and/or nurses) included telephone, clinic-based, or home care needs assessments, self-management support, medication review, and referral to services. Details of this intervention are also discussed in Flaks-Manov et al. (2020).

3. Data

We use administrative data from Clalit on all covered index hospital admissions of patients aged 60–70 to internal medicine units at any Israeli hospital during 2009–2016.[3] This sample includes 171,541 observations, each representing one index admission (2009–2016) of 95,840 unique patients to one of Israel's 28 general hospitals (including both Clalit- and non-Clalit owned hospitals). For each index admission, data contain detailed one-year healthcare utilization history prior to the admission from the Clalit data warehouse, including the predicted readmission risk scores that were available to providers in real time (Table 1).

Access to these data and the model used by Clalit to calculate risk scores for its covered beneficiaries allows us to calculate risk scores retrospectively, even for patients for whom no scores were calculated in real time (for testing, we recalculate the risk scores for patients who had risk scores calculated in real time, and obtain a near perfect correlation of 0.98). Using these risk scores, we define the subsample of *all* admissions in our sample who had high readmission risk (a score of 50 or more), including patients aged 64 or younger, for which risk scores were not calculated in real time because the intervention was restricted to patients aged 65 and older.

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[2]While hospital nurses are involved in the discharge of all patients, the novelty of the CTN role is the affiliation with the primary care division of Clalit. Internal communications included the following nonexhaustive list of suggested actions to be taken with patients identified as high-risk, prior to discharge: review the reasons for the index admission; review patient readiness for discharge; discuss post-discharge treatment options with the hospital staff responsible for the patient; contact the patient's primary care physician or a nurse in the patient's regular primary care clinic; schedule follow-up appointments with specialists; contact welfare representatives. Recent work suggests that such activities are associated with reduced 30-day readmission rates (Rayan-Gharra, Shadmi, Tadmor, Flaks-Manov, & Balicer, 2019a).

[3]The work covered in this manuscript has been conducted with the ethical approval of all relevant bodies (IRB Reference 0233–16-COM2, 24/4/2017).

Table 1. Variables used to predict readmission risk (Using the PREADM model).

Binary Variables	Percent	N (=1)	PREADM coefficient
A. All Admissions			
CHF	19.8%	29,732	0.1959
COPD	21.4%	32,021	0.1549
CRF	22.1%	33,167	0.3535
Malignancy	22.3%	33,428	0.3164
Arrhythmia	25.6%	38,432	0.2551
Disability	10.8%	16,246	0.3539
Immigrant (after 1990)	9.8%	14,669	-0.4216
Supplementary insurance	73.9%	1,10865	-0.1541
B. High-Risk Admissions			
CHF	52.9%	10,283	(same)
COPD	40.9%	7.948	
CRF	60.3%	11,721	
Malignancy	41.5%	8,072	
Arrhythmia	51.4%	9,995	
Disability	36.5%	7,103	
Immigrant (after 1990)	3.3%	645	
Supplementary insurance	65.6%	12,758	

Continuous Variables	Mean	St. Dev.	Median	Min	Max	PREADM coefficient
A. All Admissions						
Inpatient admission count (past 3 months)	0.500	0.987	0	0	17	0.2519
Community visit count (past 3 months)	3.236	3.325	2	0	18	0.0135
Narcotic prescription count (past month)	0.058	0.296	0	0	5	0.0745
Days since last admission	243.0	140.4	361	1	365	-0.0001
ACG probability of admission (within 6 months)	0.148	0.168	0.0680	0	0.9369	0.7752
Specialist visits cost (past 12 months, NIS)	697.04	935.57	401.09	0	24718	-0.0002
B. High-Risk Admissions						
Inpatient admission count (past 3 months)	1.929	1.624	2	0	17	(same)
Community visit count (past 3 months)	4.778	4.233	4	0	18	
Narcotic prescription count (past month)	0.164	0.506	0	0	4	
Days since last admission	81.86	92.41	48	1	365	
ACG probability of admission (within 6 months)	0.367	0.218	0.3693	0	0.9369	
Specialist visits cost (past 12 months, NIS)	518.47	633.63	316.41	0	7125.76	

N = 149,924 Observations, each representing one index admission of 85,958 unique patients to one of 28 hospitals. The sample for which we calculate risk scores includes admissions that occurred between 2010–2016, the period for which we have all variables for calculating scores (we exclude 21,616 index admissions from 2009, for which we are unable to calculate risk scores). CHF, COPD, and CRF are chronic conditions dummies for Congestive Heart Failure, Chronic Obstructive Pulmonary Disease, Chronic Renal Failure. ACG is the Johns Hopkins Adjusted Clinical Group case-mix system predicted probability of admission (Lemke, Weiner, & Clark, 2012). Risk score calculation also include dummies to flexibly control for regional variation in readmission.
Source: authors' calculations using Clalit Health Services data.

While we observe admissions since 2009, we only observe the full set of covariates used for calculating risk scores in real-time beginning in 2010. We therefore are only able to retrospectively calculate risk scores for 2010–2016. Out of the original 2009–2016 sample of 171,541 admissions, 149,924 admissions among 85,958 patients aged 60–70 at the month of admission occurred during 2010–2016; of these admissions, 19,453 had a high risk of readmission.

The main outcome we consider is readmissions to any hospital within 30 days of the index admission. We also consider post-discharge primary care encounters within 30 days of the index admission, readmissions within 60 and 90 days of the index admission, the length of stay during the index admission and its cost, and mortality rates within 1 year of the index admission (Table 2). High-risk admissions involve a substantially greater risk of being readmitted: 33.1% are readmitted within 30 days

Table 2. Outcome variables.

Binary Variables	Percent	N (events)	Missing values
A. All Admissions			
30-Day readmission	16.1%	27,645	0
60-Day readmission	22.4%	38,493	0
90-Day readmission	26.5%	45,490	0
One-year mortality	13.2%	19,706	22,360
B. High-Risk Admissions			
30-Day readmission	33.1%	6,444	0
60-Day readmission	45.6%	8,866	0
90-Day readmission	52.5%	10,210	0
One-year mortality	34.9%	5,850	2,692

Continuous Variables	Mean	St. Dev.	Median	Min	Max	Missing values
A. All Admissions						
Length of index stay (Days)	5.18	6.65	4	2	310	0
Time from discharge to primary care encounter (Days)	7.65	23.67	2	0	364	3,253
Total index admission cost (NIS)	9,532	13,019	6,078	0	###	0
B. High-Risk Admissions						
Length of index stay (Days)	6.17	7.76	4	2	237	0
Time from discharge to primary care encounter (Days)	9.15	24.97	3	0	356	728
Total index admission cost (NIS)	11,310	14,880	6692	0	2,46,919	0

Panel A is based on a sample of $N = 171{,}540$ observations, each representing one index admission of 95,840 unique patients to one of 28 hospitals in 2009–2016. Panel B is based on a sample of $N = 19{,}453$ observations, each representing the index admissions of 15% of patients with the highest readmission risk in 2010–2016, based on the PREADM model. The number of days until primary care encounter post-discharge is censored at one year. Data on subsequent mortality and primary care encounters are not yet available for a subset of 2016 admissions.
Source: authors' calculations using Clalit Health Services data.

(versus 16.1% for all admissions) and 52.5% are readmitted within 90 days (versus 26.5% for all admissions). They also have a much higher mortality rate than the average admission (34.9% versus 13.2%). For high-risk admissions, the index admission lasts a day longer and costs 19% more on average (NIS 11,300 versus 9,500). It takes high-risk patients slightly longer to encounter primary care providers post-discharge (mean 9.15 days versus 7.65 for all admissions), as the bulk of such encounters are office-based and require patients to travel.

Descriptive evidence shows a reduction in readmission rates among patients aged 65–70 following the intervention (Table 3). Before the intervention was initiated in 2012, 16.6% of patients aged 60–70 were readmitted within 30 days: 16.9% of patients aged 65–70, and 15.4% of patients aged 60–64. After the intervention, readmission rates for patients aged 65–70 declined to 16.5% whereas readmission rates of patients aged 60–64 slightly increased, to 15.5%. These changes are starker during the first period after the intervention, during which the Ministry of Health provided incentive payments for reducing readmission rates, and among high-risk patients, which the intervention specifically targeted.

4. Empirical strategy

Because the intervention targeted elderly patients, risk scores were only calculated for admissions of patients whose age at the index admission was 65 or older (N = 97,537 admissions). We rely on this specific age cutoff and use as a comparison group patients aged 60–64, whose age at the time of admission was just below this cutoff, and therefore

Table 3. Readmission rates by age group and period.

	Period			
	Before		After	
Sample	09Q1–'12Q2	12Q3–'16Q4	12Q3–'14Q2	14Q3–'16Q4
A. All Admissions				
Old (65–70)	16.9%	16.5%	16.3%	16.6%
	(0.2%)	(0.2%)	(0.2%)	(0.2%)
Young (60–64)	15.4%	15.5%	15.8%	15.2%
	(0.2%)	(0.2%)	(0.3%)	(0.2%)
B. Highest Risk Admissions (top 15%), 2010 onward				
Old (65–70)	33.3%	31.8%	31.4%	32.1%
	(0.7%)	(0.5%)	(0.8%)	(0.7%)
Young (60–64)	34.3%	34.5%	36.7%	32.9%
	(1.0%)	(0.7%)	(1.1%)	(0.9%)

Standard errors in parentheses. All-cause 30-day readmission rates, for Old and Young (patients aged 65–70 and 60–64 respectively). Before and After refer to periods before and after the beginning of the intervention, in July 2012. We further break After into two periods: 2012Q3–2014Q2, when incentives from the Ministry of Health were in place, and 2014Q3–2016Q4, when they were no longer in place.
Source: authors' calculations using Clalit Health Services data.

for whom no risk scores were calculated in real time (the real-time availability of risk scores is shown in Appendix Figure A1). The aim of this comparison is to account for potentially unobserved time trends in readmission rates and in other outcomes.

We estimate variants of the following model:

$$Y_{it} = \delta_0 + \delta_1 After_t + \delta_2 Old_t + \delta_3 After_t \times Old_i + \delta_4 X_{it} + \varepsilon_{it}, \qquad (1)$$

where i indexes admissions and t indexes periods (quarters); Y_{it} is one of the several outcomes, including readmission at various horizons, length of stay, index admission cost, and mortality (Table 2). Each outcome is evaluated separately. The variables Old_i and $After_t$ are indicators for the patient's being age 65–70 (rather than 60–64), and for the period's being after the intervention was initiated (rather than before). X_{it} includes controls for hospital, patient demographic characteristics, admission-related information, and, in some specifications, flexible time trends (which, being more flexible, subsumes $After_t$). The parameter of interest is δ_3, which is the impact of the program on outcomes.

Because the Ministry of Health's scheme was discontinued in 2014, 2 years after the program started, we compare mean outcomes separately for the first 2 years of the program and the subsequent years, by including, where appropriate, two separate indicator variables: $After_1$, for the period from the beginning of the intervention until the discontinuation of national incentives (2012Q3–2014Q2), and $After_2$, for the subsequent period (2014Q3–2016Q4). The identification assumption is that time trends affecting both age groups would have been similar in the absence of the intervention.

To test the robustness of our results to the parallel-trends assumption, we use a triple difference design and compare the difference-in-differences in outcomes of patients aged 65–70 with high risk of readmission to the difference-in-differences in outcomes among patients aged 65–70 with lower risk. Formally, we estimate a version of Equation (1) with the triple interaction term $Old_i \times After_t \times HighRisk_{it}$, where $HighRisk$ denotes

admissions with a risk score of 50 or more, as discussed earlier. As in Equation (1), all other interactions among these three variables are also included. Such a test requires the retrospective calculation of risk scores for the group aged 60–64, for which we use the same data and predictive model that were originally used to calculate the scores in real time. We also compare these triple-difference estimates with estimates of Equation (1) obtained using only the subsample of high-risk admissions over 2010–2016.

To study the impact of providing risk-scores to primary care providers during the first 30 days after discharge, we used a Kaplan-Meier estimator of the hazard of a primary care encounter, separately for patients aged 60–64 and 65–70, before and after the start of the intervention in 2012. We define patients to be at risk starting from the date of discharge and the event being any encounter with a primary care provider. We censor deaths and readmission events. To compare the survival distributions between age groups in each period, we use the log-rank test.

5. Results

During its first 2 years, the intervention was associated with a 5.9% reduction of 30-day readmission rates of patients aged 65–70 (a 1.0 percentage point reduction from a baseline readmission rate of 16.9%; p = 0.001; Table 4), relative to the comparison group of patients aged 60–64. The effect of the intervention was the largest among the target population of high-risk patients. Among high-risk patients, readmission rates were reduced by 12.3–12.6% from a baseline of 33.3% (p = 0.004). After the first 2 years, when

Table 4. Readmission rates and intervention status, difference-in-differences estimates.

| | 30-Day Readmission | | | |
| | All | | High-Risk | |
Quarter and Hospital Dummies	No	Yes	No	Yes
Old x After (First 2 Years)	-0.010***	-0.010***	-0.042***	-0.041***
	(0.003)	(0.003)	(0.014)	(0.014)
Old x After (Subsequent Years)	-0.001	-0.002	0.003	0.003
	(0.004)	(0.004)	(0.013)	(0.013)
Old	0.015***	0.015***	-0.01	-0.012
	(0.002)	(0.002)	(0.011)	(0.011)
After (First 2 Years)	0.005*		0.023	
	(0.002)		(0.015)	
After (Subsequent Years)	-0.002		-0.015	
	(0.004)		(0.013)	
Observations (Admissions)	1,71,540	1,71,540	19,453	19,453
Clusters (Hospitals)	28	28	27	27
Mean dependent variable	0.161	0.161	0.331	0.331
Model rank	6	62	6	57
Adjusted R Square	0.0003	0.003	0.001	0.005

Standard errors clustered by hospital in parentheses. *p < 0.1; **p < 0.05; ***p < 0.01. Old and Young refer to patients aged 65–70 and 60–64 respectively. Before and After refer to periods before and after the beginning of the intervention, in July 2012. We further break After into two periods: 2012Q3–2014Q2, when incentives from the Ministry of Health were in place, and 2014Q3–2016Q4, when they were no longer in place. High risk refers to the 15% of patients with the highest readmission risk, based on the PREADM model.
Source: authors' calculations using Clalit Health Services data.

incentive payments from the Ministry of Health were discontinued, the difference in readmission rates between the age groups of 60–64 and 65–70 gradually declined (Figure 1). Clalit did continue the calculation and dissemination of risk scores after the
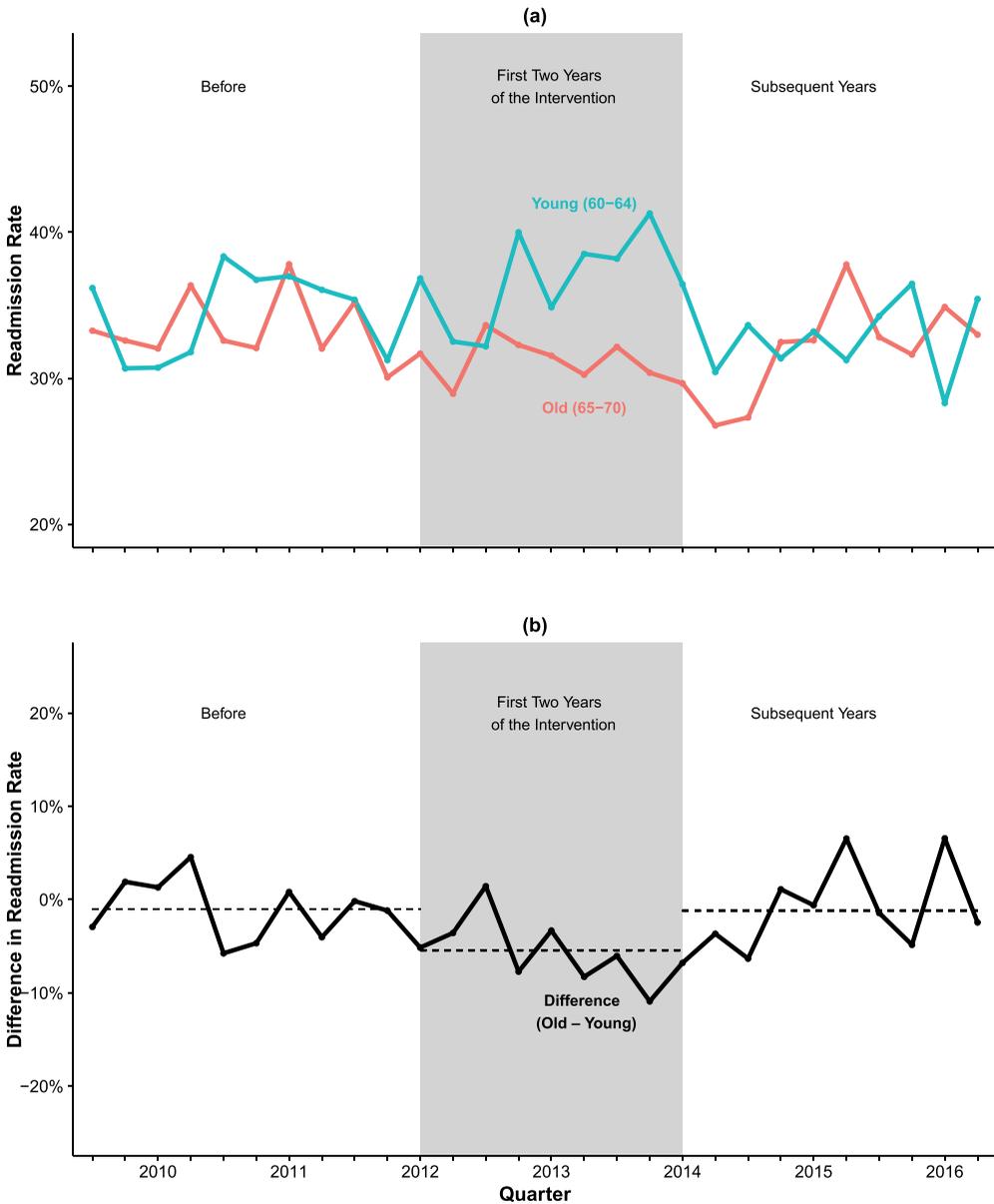
(a)

Figure 1. Readmission rates by age group over time, high-risk patients. $N = 19,453$ admissions from 2010 to 2016 with predicted readmission risk score of 50 or more (top 13% of the risk distribution, mean readmission rate 33%). Panel (a) shows quarterly 30-day readmission rates for patients aged 65–70 (Old) and 60–64 (Young). Panel (b) shows the difference in readmission rates between these age groups. The horizontal-dashed lines in panel (b) mark the average difference for each of the three periods studied. This difference is statistically significant for the first 2 years after the program start (See Table 4). Results for all admissions are shown in Figure A7. Source: authors' calculations using Clalit Health Services data.

first 2 years, but conversations with Clalit employees suggest that it was followed by a drop in managerial attention, with divisions shifting their attention toward other policy goals, which could explain the washout of the initial effect. Results are robust to flexibly controlling for time trend in admissions, using quarterly dummies (Table 4). Results are also robust to redefining our age groups by excluding patients aged 65 or between 64 and 65 upon the index admission (Appendix Table A1).

Evidence supports the parallel trends assumption. Readmission rates of high-risk patients from both age groups did not exhibit distinguishable trends prior to the intervention. Furthermore, the estimated reduction in readmission among high-risk patients obtained using a triple-difference specification (Table 5), in which high-risk cases are compared against low-risk ones, is 13.6% (p = 0.001), similar to DD estimates obtained using only the sub-sample of high-risk patients (12.3–12.6%). Results are also robust to controlling for multiple additional factors, including demographics, index admission characteristics, and readmission risk scores.

Table 5. Readmission rates and intervention status, DDD estimates.

| | 30-Day Readmission | | |
| | Baseline | | Patient Controls |
Quarter and Hospital Dummies	No	Yes	Yes
Old x After (First 2 Years) x High-Risk	-0.042***	-0.042***	-0.046***
	(0.014)	(0.014)	(0.014)
Old x After (Subsequent Years) x High-Risk	-0.003	-0.002	-0.007
	(0.014)	(0.014)	(0.014)
Old	0.005*	0.005*	-0.001
	(0.003)	(0.003)	(0.005)
High-Risk	0.211***	0.209***	0.029**
	(0.012)	(0.012)	(0.012)
After (First 2 Years)	0.001	0.039	0.063
	(0.003)	(0.068)	(0.064)
After (Subsequent Years)	-0.002	0.037	0.050*
	(0.004)	(0.03)	(0.03)
Old x High-Risk	-0.015	-0.015	-0.005
	(0.011)	(0.011)	(0.011)
Old x After (First 2 Years)	-0.0003	-0.0001	0.002
	(0.004)	(0.004)	(0.004)
Old x After (Subsequent Years)	0.005	0.005	0.008**
	(0.003)	(0.004)	(0.004)
High-Risk x After (First 2 Years)	0.023	0.023	0.023
	(0.016)	(0.016)	(0.015)
High-Risk x After (Subsequent Years)	-0.013	-0.014	-0.012
	(0.014)	(0.014)	(0.014)
Observations (Admissions)	1,49,924	1,49,924	1,49,924
Clusters (Hosptials)	28	28	28
Mean dependent variable	0.161	0.161	0.161
Model rank	12	64	153
Adjusted R Square	0.032	0.034	0.056

Standard errors clustered by hospital in parentheses. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$. Triple-difference (Difference in Difference in Differences) estimates of the impact of the program on 30-day readmission rates for two periods: the first 2 years of the intervention and subsequent years. Columns (1) and (2) show the baseline specifications with and without controls for hospital and quarter dummies. Column (3) contains additional controls for the following variables: demographics (age, gender, district, and dummy for supplementary insurance), index admission's characteristics (hospital, ward, dummies for elective admission and Clalit-owned hospital, length of admission), and readmission-risk score. $N = 149,924$ index admissions from 2010–2016 (we exclude 21,616 index admissions from 2009, for which we are unable to calculate risk scores).
Source: authors' calculations using Clalit Health Services data.

This evidence notwithstanding, we emphasize that results do not rule out the possibility of negative spillovers, whereby the increased attention toward patients with (high) risk scores came at the expense of reduced attention to younger high-risk patients for which scores were not calculated. Spillovers pose a general risk associated with score-based targeting strategies. Prospective evaluations should be designed to account for them (Angelucci & Di Maro, 2015), and their mitigation should be considered together with other issues arising with the use of algorithms in healthcare (Obermeyer, Powers, Vogeli, & Mullainathan, 2019; Rambachan, Kleinberg, Mullainathan, & Ludwig, 2020).

We find no evidence for selective readmission around the 30-day policy target (cf., Gupta, 2017). During its first 2 years, the decline in 30-day readmission rates was accompanied by declines in 60- and 90-day readmission rates among patients aged 65–70 relative to patients aged 60–64 (by 5.9%, p = 0.0066, and 7.1%, p = 0.0001, respectively; Appendix Table A1). The intervention was neither associated with any significant change to the index-admission length (Appendix Table A2) nor the total index admission cost (Appendix Table A3). One-year mortality decreased overall, albeit the decrease is not statistically significant among high-risk cases (− 9.2% for all cases, p = 0.0063; − 11.3% for high-risk cases, p = 0.1834, Appendix Table A4). Overall, the reduction in readmission rates does not appear to be driven by changes to the timing of discharge or admission by hospitals.

The intervention aimed to improve care continuity by communicating risk scores to primary care clinics post-discharge, with the goal of improving the timeliness of follow-up encounters for discharged patients. Survival analysis suggests that communicating readmission risk scores of newly discharged patients to primary care providers did in fact expedite post-discharge primary care encounters: before the intervention, the estimated hazard rate for post-discharge primary care encounters (conditional on no readmission or death) did not differ significantly between patients aged 65–70 and 60–64 (log-rank: $p = 0.16$); after the intervention, it was significantly higher (log-rank: $p < 0.0001$) for patients aged 65–70 Figure 2.[4] Figure 3 shows the estimated rates of post-discharge encounters by type of service. Both office-based encounters (which include encounters such as a physician office visit or an encounter with a primary care nurse in a clinic) and remote encounters (which include phone calls and related events done without the presence of the patient, such as prescription adjustment via online channels) exhibited a similar pattern. Before the intervention, the rate of both types of visits did not differ significantly between patients aged 65–70 and patients aged 60–64 (log-rank: $p = 0.86$ for office-based, $p = 0.28$ for remote), but after the intervention, both rates were significantly higher for patients aged 65–70 (log-rank: $p < 0.0001$ for office-based, $p < 0.0021$ for remote). However, like the reduction in readmission rates, the difference in the rates of post-discharge primary care encounters (of each type and overall) also decreased in magnitude after the Ministry of Health's scheme was discontinued (log-rank: $p = 0.017$). This association suggests that expediting follow-up encounters contributed to the reduction in readmission rates. The protective effect of primary care encounters on readmission risk, beyond the baseline risk score, is also shown in Rayan-Gharra, Balicer, Tadmor, and Shadmi (2019b).

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[4]Appendix Figure A2 shows the results of the same analysis grouped by age group, rather than by period, to allow for within-age-group comparison of rates over time. It shows that the probability of post-discharge encounters decreased after the intervention for patients aged 65–70 ($p = 0.013$), but not for patients aged 60–64 ($p = 0.16$).
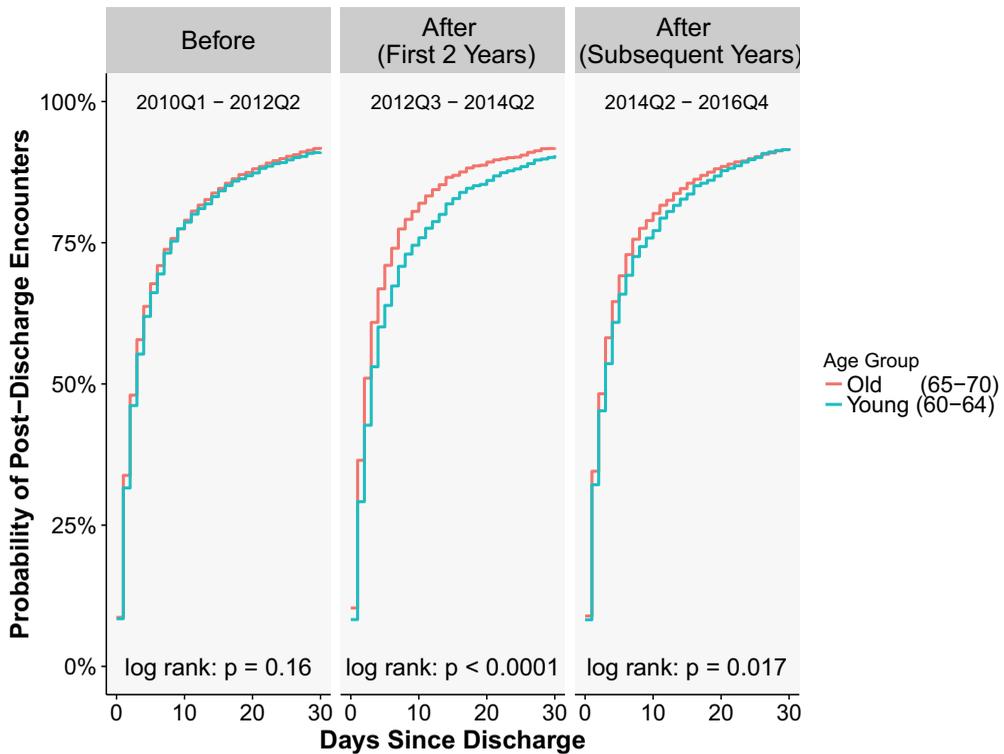
Figure 2. Survival estimates of the probability of post-discharge encounters with primary care providers (high-risk admissions). Figure shows Kaplan-Meier estimator of the probability of primary care encounters as a function of days since discharge. At-risk observations at day t are all cases not readmitted, dead, or having had encountered primary care providers by day t after discharge. The panels show estimates for three separate time periods: before the intervention started; its first 2 years, when the Ministry of Health's scheme was in place; and subsequent years. This figure shows results for the sample of high-risk admissions. Appendix Figure A8 shows results for all admissions. Source: authors' calculations using Clalit Health Services data.

6. Heterogeneity analyses

In this section, we report the results of additional analyses we have performed to study the heterogeneity of our main estimates over several dimensions.

First, to assess the heterogeneity with regard to age, we examine the impact of the intervention over age groups that extend beyond the baseline sample of patients aged 60–70. Namely, in addition to the two original age groups (i.e., 60–64 years old, which we refer to as "Young"; and 64–70 years old, which we refer to as "Old") we consider all younger patients (25–59 years old, which we refer to as "Very Young"), for which no risk scores were calculated in real time, and older patients (>70 years old, which we refer to as "Very Old"), for which score were calculated.

Appendix Figure A3 shows readmission rates of high-risk admissions for the original and these additional age groups. Results show that the Very Young age group, like the Young age group in our main sample, for which no risk scores were calculated in real time, experienced higher rates of readmissions in the 2 years following the intervention,
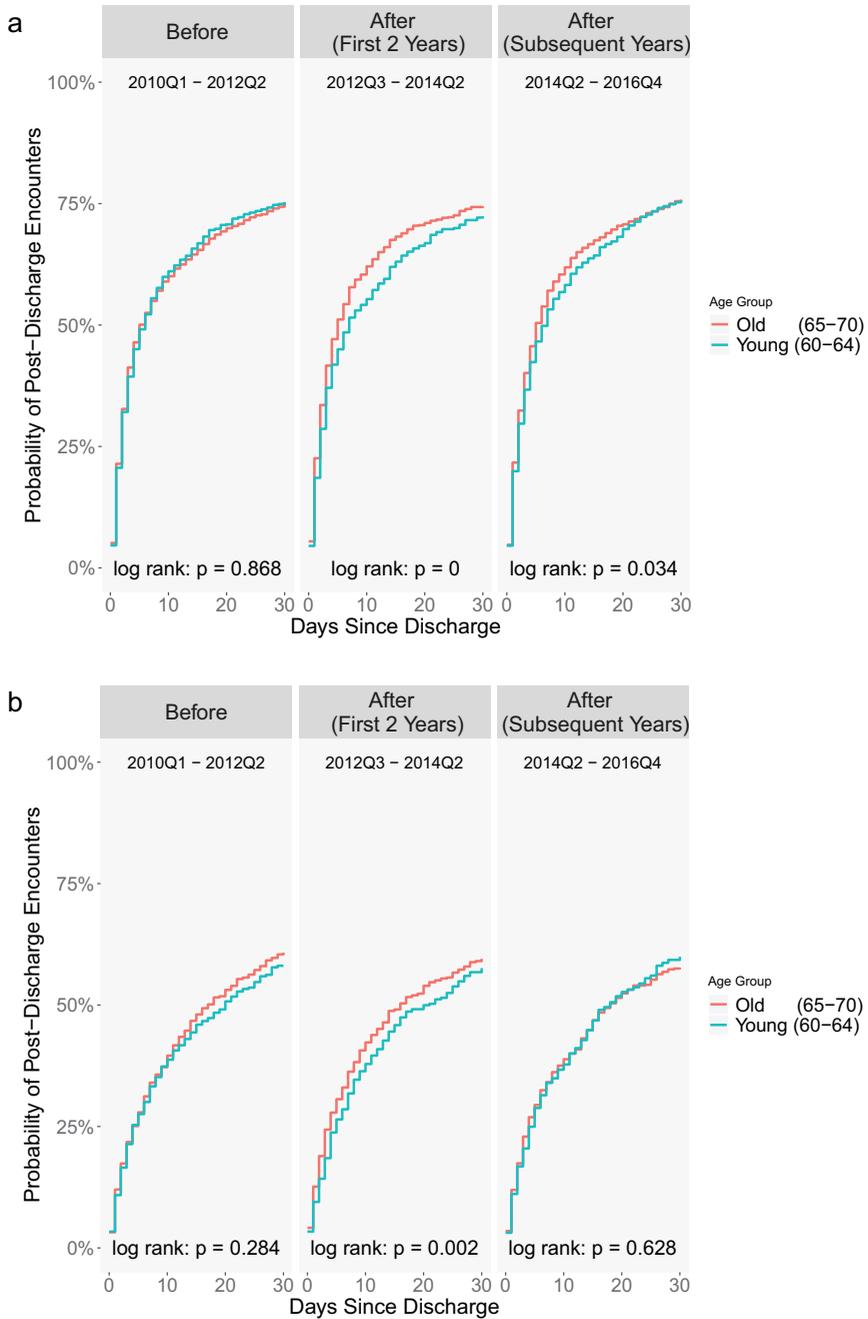
Figure 3. Survival estimates of the probability of post-discharge encounters with primary care providers, by type of encounter (high-risk admissions). Figure shows Kaplan-Meier estimator of the probability of primary care encounters as a function of days since discharge. At-risk observations at day *t* are all cases not readmitted, dead, or having had encountered primary care providers by day *t* after discharge. The panels show estimates for three separate time periods: before the intervention started; its first 2 years, when the Ministry of Health's scheme was in place; and subsequent years. Source: authors' calculations using Clalit Health Services data.

compared to the Old (65–70 year old) patients, for which risk scores were calculated. Appendix Figure A4 shows post-discharge encounters for the same groups. While both Very Young and Very Old patients tend to have lower rates of post-discharge primary care encounters, which likely reflect baseline differences in morbidity and utilization patterns among the different age groups, among the two additional age groups we see a similar effect of the intervention, with the rate of post-discharge encounters increasing among the Very Old relative to the Very Young in the periods following the intervention.

We further estimate the difference-in-differences model specified in Equation (1) separately by district and by hospital. Results are summarized in Appendix Figures A5 and A6, where districts and hospitals are sorted by size in descending order. The reduction in readmission rates among patients aged 65–70 relative to patients aged 60–64 appears similar across districts (administrative divisions of primary care) and across most large hospitals, though hospital-level estimates are naturally noisier due to the smaller sample sizes.

7. Conclusion

We use detailed administrative and EHR from 2009 to 2016 on a sample of 171,541 hospital admissions to retrospectively analyze the impact of a large-scale intervention to reduce hospital readmission rates in Israel. Comparing admissions of patients aged 65–70 with admissions of patients aged 60–64, for whom risk scores were not calculated, we found that providing individual patient risk scores to hospital staff, designated care transition nurses, and primary care providers post-discharge is associated with a significant reduction in 30-day readmission rates among patients targeted by the intervention and leads to more-timely interactions of such patients with primary care providers post-discharge, particularly among high-risk patients. Furthermore, we present evidence that the intervention was also associated with a decline in 60- and 90-day readmission rates, and with no changes to index admission length and cost, suggesting that readmissions were not strategically deferred around the 30-day mark, and that reduced readmission rates did not come at the cost of increased overall hospital utilization.

Overall, our results suggest that real-time individual risk scores can help allocate clinicians' attention to patients with high readmission risk and improve transitional care management, resulting in fewer readmissions. However, the fact that effects declined after financial incentives had been discontinued also suggests that risk scores should be used on an ongoing basis and accompanied by a comprehensive approach that provides ongoing oversight and motivation for readmission reduction (Balicer, Shadmi, & Israeli, 2013; Epstein, Jha, & Orav, 2011).

As we discussed, one limitation of the difference-in-difference approach is that it does not separately identify negative spillovers, namely a situation in which increased attention toward patients with (high) risk scores came at the expense of reduced attention to high-risk patients for which scores were not calculated. Such a spillover would affect the interpretation of our DD estimates, as a decrease in readmission rate of high-risk patients aged 65–70 would be partly offset by a possible increase in the readmission rate of high-risk patients aged 60–64, so estimates might not reflect the full incidence of the program on the untreated.

Yet, the main takeaway from our analysis remains intact despite this concern. Specifically, our analysis suggests that, coupled with appropriate incentives, the provision of risk scores had a noticeable impact on provider and system priorities. While this impact may not have been entirely generated by increased attention overall but instead been generated by shifting attention from one group of patients to another, it still illustrates that risk scores can effectively divert the attention of providers and effectively altered the priority with which patients with high-risk scores were treated. This suggests that a nontrivial share of high-risk readmissions are preventable, and that increased focus or attention can play an important role in reducing readmission rates, thus making the combination of risk scores and staffing decisions powerful instruments for optimizing readmission rates at scale.

The reduction in readmission rates brought about by this intervention in Israel is of comparable magnitude to the estimated reduction in readmission rates in the United States associated with HRRP penalties over the same period, 2012–14 (Gupta, 2017). An interesting question for future research is whether targeting of high-risk patients can further improve these and other ongoing readmission reduction efforts.

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