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# Cat Targeting High-Risk Patients Reduce Readmission Rates? Evidence from Israel

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**Abstract**

We study a large intervention to reduce hospital readmission rates in Israel. Since 2012, readmission risk was calculated for patients aged 65 and older, and high risk patients 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 scores were calculated. The largest reduction, 12.3%, was among high-risk patients. Primary care post-discharge follow-up encounters were significantly expedited. The magnitude of the estimated effect peaked during the first two years, and it declined subsequently, after government incentives to reduce readmission rates were discontinued. Taken together, the evidence demonstrates that informing providers about patient risk in real time can improve care continuity and reduce hospital readmissions, and that maintaining such efforts on an ongoing basis is important.

Keywords: Healthcare, Hospital Readmissions, Predictive Modeling
JEL Codes: I10, I18

# I 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 US, the Hospital Readmissions Reduction Program (HRRP) imposes penalties on hospitals based on their performance on readmissions since 2012 (so far, penalties surpassed $1.3 billion), and in the UK, readmissions are no longer separately reimbursed since 2011 (Kristensen et al., 2015). These incentives intensified providers' efforts to reduce hospital readmissions (Mellor et al., 2017). Readmission reduction interventions increasingly incorporate risk prediction algorithms to prioritize high-risk individuals (Burke and Coleman, 2013; Kripalani et al., 2014; Zhou et al., 2016). Nonetheless, limited evidence exists regarding the effectiveness of prioritizing patients based on predictive modeling.

To address this gap, we examined 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 pre-trained model (Shadmi et al., 2015). The score was routinely calculated for all 1.5 million 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 towards patients of 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 would reduce readmission rates. Although the Ministry of Health incentive program was discontinued in 2014, two 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 studied the impact of financial incentives and quality interventions on readmission reduction in other contexts (see 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 ones (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 facilitated 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 record (EHR) data on the history each patient allow us to separately study the impacts on patients with the top 15% readmission risk (the internal definition for "high risk patients"), by retrospectively calculating the risk scores of patients aged 60–64 and using a triple-difference design.

Within the first two years after the intervention was initiated (2012–2014), readmission rates among the 65-70 year old patients have 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). 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 65–70 year old patients had similar probability and timing of post-discharge primary-care encounters as the 60–64 year old patients, after the intervention (which included notifying primary care providers of their discharged patients' risk scores), 65–70 year or patients have significantly higher chance of having a community 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, e.g., by inefficiently extending the length of the index admission, by deferring readmissions to just beyond the 30-day mark (Gupta, 2017), or by 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 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 two years of the intervention, while the Ministry of Health incentives were in place. They subsequently declined, after these incentives were discontinued.

Results suggest that communicating risk scores to hospital and primary care providers can help focus organizational efforts to achieve readmission reduction in high-risk populations. However, the decline in 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 II discusses institutional background. Sections III and IV describes the data and empirical strategy. Section V discusses the results. Section VI concludes.

# II Institutional Background

The readmission reduction program we study was implemented in Clalit Health Services, one of four non-for-profit integrated healthcare financing and delivery organizations in Israel, which covers over four million members (about 54% of the market share). 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 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 patient of any age to any hospital in Israel that lasted two or more night 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 on December 2011. It was in effect 2012–2013 and discontinued afterwards.

To address these ambitious goals of the Israeli Ministry of Health program, in 2012, Clalit developed and deployed an intervention for reducing readmission rates among its covered patients. The intervention had three parts. 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 unit of general hospitals (the development and validation of this model are discussed in Shadmi et al., 2015). 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 admission. 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). Though the incentives by the Ministry of Health applied to patients of all ages, scores were only calculated for patients aged 65 an 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 arbitrary age cutoff in our analysis.

The second part of the intervention included, from mid-2012, the introduction of a new role of care transition nurses (CTNs). CTNs were instructed to work down the list of the PREADM scores, and devote particular attention to patients of the highest risk for readmission.[1] Though no formal cut-off 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 top 15% of patients with the highest 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 she has not already herself identified the patient. Because Clalit patients can be admitted to any hospital in Israel—not just to hospitals owned by Clalit—special EHR system were incorporated to communicate

[1]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 non-exhaustive 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.

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 score, via push notifications, to primary care clinics of discharged patients. These clinics were instructed contact high-risk patients for follow up within 48 hours of discharge. Structured follow-up by the primary care clinics staff (physicians and/or nurses) included telephone, clinic-based, or home care needs assessments, self-management support, medication review and referral to services.

# III Data

We use administrative data from Clalit on all covered index hospital admissions of 60–70 year-old patients to internal medicine units at any Israeli hospital during 2009–2016.[2] 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 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 allowed us to calculate risk scores retrospectively, even for patients for whom no scores were calculated in real time (for testing, we recalculated the risk scores for patients which risk scores were calculated in real time, and obtained a near perfect correlation, $\rho = 0.98$). Using these risk scores, we define the subsample of *all* admissions in our sample who had high readmission risk (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.

[2]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).

While we observe admissions since 2009, we only observe the full set of covariates used for calculating risk scores in real time beginning 2010. We therefore are only able to retrospectively calculate risk scores for the period 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 high risk of readmission.

The main outcome we consider is readmissions to any hospital within 30-day of the index admission. We also consider post-discharge primary care encounters within 30-day of the index admission, readmissions within 60 and 90 days of the index admission, the length of stay during the index admission, and mortality rates within one year of the index admission (Table 2).

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

# IV 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 the arbitrariness of the specific age cutoff and use as comparison group patients aged 60–64, whose age at the time of admission was just below this arbitrary cutoff, and therefore for whom no risk scores were calculated in real-time (the real-time availability of risk scores is shown in Figure A2). 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:

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

where $i$ indexes admissions and $t$ indexes periods (quarters), $Y_{it}$ is one of several outcomes, including readmission at various horizons, length of stay, and mortality (Table 2). Each outcome is evaluated separately. The variables $Old_i$ and $After_t$ are indicators for the patient being of age 65–70 (rather than 60–64), and for the period 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 $\delta_3$, the impact of the program on outcomes.

Because the Ministry of Health's scheme was discontinued in 2014, two years after the program started, we compare mean outcomes separately for the first two years of the program and the remaining subsequent years, by including, where appropriate, two separate dummies: $After_1$, for the period from the beginning of 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 65–70 year-old patients with high risk of readmission to the difference-in-differences in outcomes among 65–70 year-old patients with low risk. Formally, we estimate a version of model (1) with the triple interaction term $Old_i \times After_t \times HighRisk_{it}$, where $HighRisk$ denotes admissions with risk score of 50 or more (the top 15% of risk, with average readmission rate of 33%). As in model (1), all other interactions among these three variables are also included. Such a test requires the retrospective calculation of risk scores for the age group 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 model (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 provider, separately for 60–64 and 65–70 year-old patients, before and after the intervention initiation 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.

# V Results

During its first two years, the intervention was associated with a 5.9% reduction of 30-day readmission rates of patients aged 65–70 (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 two years, when incentive payments from the Ministry of Health were discontinue, the difference in readmission rates between the age group 60–64 and 65–70 has gradually declined (Figure 1). Result 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 years old or 64–65 years old upon the index admission (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 patient 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 controlling for multiple additional factors, including demographics, index admission characteristics, and readmission-risk score.

We find no evidence for selective readmission around the 30-day policy target (cf., Gupta, 2017). During its first two years, the decline in 30-day readmission rates, was accompanied by declines in 60- and 90-day readmission rates among 65–70 relative to 60–64 year-old patients (by 5.9%, p = 0.0066, and 7.1%, p = 0.0001, respectively; Table A1). Neither the intervention was associated with any significant change to the index-admission length (Table A2). 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, Table A3). 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 expedited post-discharge primary care encounters: before the intervention, the estimated hazard rate for post-discharge community care encounters (conditional on no readmission or death) did not differ significantly between 65–70 and 60–64 year-old patients (log-rank: $p = 0.16$)); after the intervention it was significantly higher (log-rank: $p < 0.0001$) for 65–70 year-old patients (Figure 2). However, like the reduction in readmission rates, this difference too 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.

# VI Conclusion

We use detailed administrative and EHR from 2009–2016 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 65–70 year-old patients with admissions of 60–64 year-old patients, 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 and leads to more timely interactions of patients with community providers post-discharge, particularly among high-risk patients. Furthermore, 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, suggests 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, results suggest that real-time individual risk scores can help allocate clinicians attention to patients of 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 the use of risk scores should be maintained on an ongoing basis, and accompanied by a comprehensive approach that provides ongoing oversight and motivation for readmission reduction (Epstein et al., 2011; Balicer et al., 2013).

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 US 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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# Tables and Figures

Table 1: Variables Used to Predict Readmission Risk (Using the PREADM Model)

| Binary Variables | Percent | N (=1) | Linear coefficient | | | |
|---|---|---|---|---|---|---|
| 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% | 110,865 | -0.1541 | | | |
| Continuous Variables | Mean | St. Dev. | Median | Min | Max | Linear coefficient |
| Inpatient admission count (past 3 months) | 0.4996 | 0.9869 | 0 | 0 | 17 | 0.2519 |
| Community visit count (past 3 months) | 3.2358 | 3.3253 | 2 | 0 | 18 | 0.0135 |
| Narcotic prescription count (past month) | 0.0582 | 0.2962 | 0 | 0 | 5 | 0.0745 |
| Days since last admission | 243.04 | 140.37 | 361 | 1 | 365 | $-0.0001$ |
| ACG probability of admission (within 6 months) | 0.1475 | 0.1676 | 0.0680 | 0 | 0.9369 | 0.7752 |
| Specialist visits cost (past 12 months, NIS) | 697.04 | 935.57 | 401.09 | 0 | 24718 | $-0.0002$ |

*Notes:* N = 149,924 Observations, each representing one index admission (2010–2016, for which we have all variables for calculating risk scores) of 85,958 unique patients to one of 28 hospitals. CHF, COPD, 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 et al., 2012). Risk score calculation also included dummies to flexibly control for regional variation in readmission. Source: authors' calculations using Clalit Health Services data.

Table 2: Outcome Variables

| Binary Variables | Percent | N (events) | Missing values | | | |
|---|---|---|---|---|---|---|
| 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 | | | |
| **Continuous Variables** | **Mean** | **St. Dev.** | **Median** | **Min** | **Max** | **Missing values** |
| Number of days | | | | | | |
| Length of index stay | 5.18 | 6.65 | 4 | 2 | 310 | 0 |
| From discharge to primary care encounter | 7.65 | 23.67 | 2 | 0 | 364 | 3,253 |

*Notes:* N = 171,540 Observations, each representing one index admission (2009–2016) of 95,840 unique patients to one of 28 hospitals. The number of days until community encounter post-discharge is censored at one year. Data on subsequent mortality and community-based encounters are not yet available for a subset of 2016 admissions. Source: authors' calculations using Clalit Health Services data.

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%) | (0.7%) | (1.1%) | (0.9%) |

*Notes:* s.e. 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 to two period: 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.

Table 4: Readmission Rates and Intervention Status, Difference-in-Differences Estimates

| | 30-Day Readmission | | | |
|---|---|---|---|---|
| | All | | High-risk only | |
| Quarter and Hospital Dummies | No | Yes | No | Yes |
| | (1) | (2) | (3) | (4) |
| Old × After (First Two Years) | $-0.010^{***}$ | $-0.010^{***}$ | $-0.042^{***}$ | $-0.041^{***}$ |
| | (0.003) | (0.003) | (0.014) | (0.014) |
| Old × After (Subsequent Years) | $-0.001$ | $-0.002$ | 0.003 | 0.003 |
| | (0.004) | (0.004) | (0.013) | (0.013) |
| Old | $0.015^{***}$ | $0.015^{***}$ | $-0.010$ | $-0.012$ |
| | (0.002) | (0.002) | (0.011) | (0.011) |
| After (First Two Years) | $0.005^{*}$ | | 0.023 | |
| | (0.002) | | (0.015) | |
| After (Subsequent Years) | $-0.002$ | | $-0.015$ | |
| | (0.004) | | (0.013) | |
| Observations (Admissions) | 171,540 | 171,540 | 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 $R^2$ | 0.0003 | 0.003 | 0.001 | 0.005 |

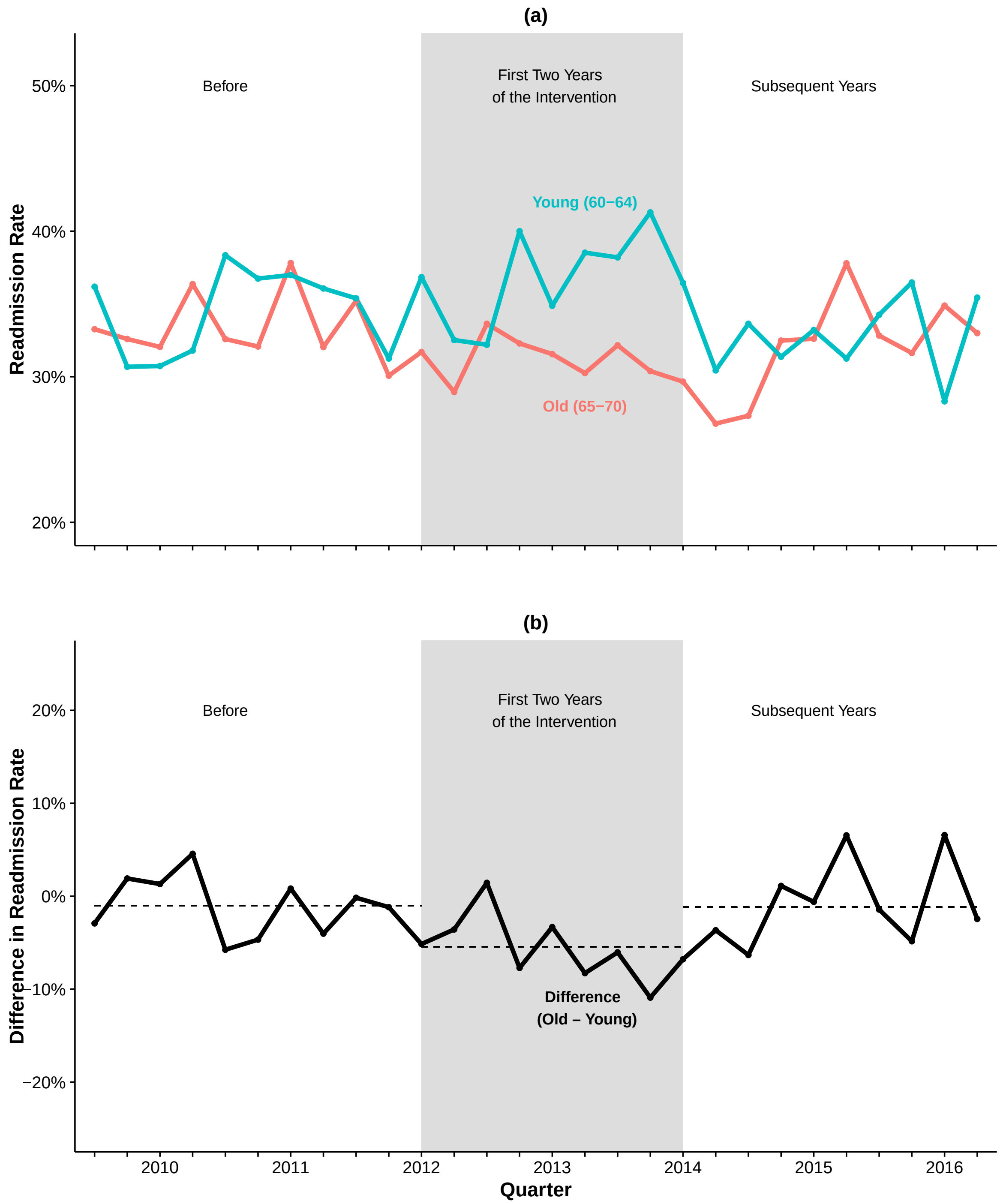
*Notes:* S.E. clustered by hospital in parentheses. $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01. Old and Young refer to patients aged 65–70 and 60–64 respectively. Before and After refer to periods before and after the beginning of the intervention, in July 2012. We further break After to two period: 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 15% of patients with the highest readmission risk, based on the PREADM model. Source: authors' calculations using Clalit Health Services data.

Table 5: Readmission Rates and Intervention Status, DDD Estimates

| | 30-Day Readmission | | |
|---|---|---|---|
| | Baseline | | Patient Controls |
| Quarter and Hospital Dummies | No | Yes | Yes |
| | (1) | (2) | (3) |
| Old × After (First Two Years) × High-Risk | $-0.042^{***}$ | $-0.042^{***}$ | $-0.046^{***}$ |
| | (0.014) | (0.014) | (0.014) |
| Old × After (Subsequent Years) × 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 Two Years) | 0.001 | 0.039 | 0.063 |
| | (0.003) | (0.068) | (0.064) |
| After (Subsequent Years) | $-0.002$ | 0.037 | $0.050^{*}$ |
| | (0.004) | (0.030) | (0.030) |
| Old × High-Risk | $-0.015$ | $-0.015$ | $-0.005$ |
| | (0.011) | (0.011) | (0.011) |
| Old × After (First Two Years) | $-0.0003$ | $-0.0001$ | 0.002 |
| | (0.004) | (0.004) | (0.004) |
| Old × After (Subsequent Years) | 0.005 | 0.005 | $0.008^{**}$ |
| | (0.003) | (0.004) | (0.004) |
| High-Risk × After (First Two Years) | 0.023 | 0.023 | 0.023 |
| | (0.016) | (0.016) | (0.015) |
| High-Risk × After (Subsequent Years) | $-0.013$ | $-0.014$ | $-0.012$ |
| | (0.014) | (0.014) | (0.014) |
| Observations (Admissions) | 149,924 | 149,924 | 149,924 |
| Clusters (Hosptials) | 28 | 28 | 28 |
| Mean dependent variable: | 0.161 | 0.161 | 0.161 |
| Model rank: | 12 | 64 | 153 |
| Adjusted $R^2$ | 0.032 | 0.034 | 0.056 |

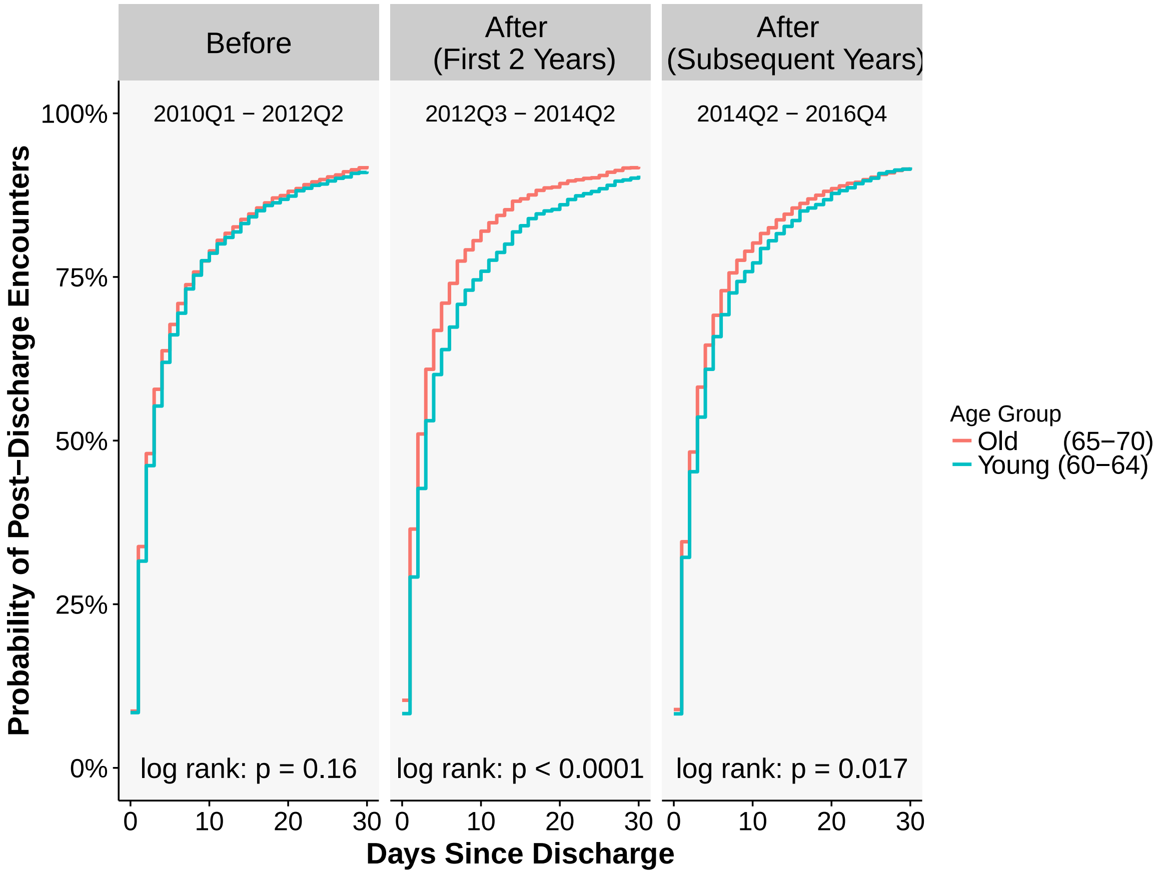
*Notes:* S.E. clustered by hospital in parentheses. $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01. Triple-difference (Difference in Difference in Differences) estimates of the impact of the program on 30-day readmission rates for two periods: the first two years of the intervention, and subsequent years. Columns (1) and (2) show the baseline specifications with and without controls for hosptials and quarter dummies (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. Source: authors' calculations using Clalit Health Services data.

Figure 1: Readmission Rates by Age Group Over Time, High-Risk Patients




*Notes:* N = 19,453 admissions 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 two years after the program start (See Table 4). Source: authors' calculations using Clalit Health Services data.

Figure 2: Survival Estimates of the Probability of Post-Discharge Encounters with Community Care Providers (High Risk Admissions)




*Notes:* Kaplan-Meier estimator of the probability of community 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 community care providers by day $t$ after discharge. The panels show estimates for three separate time periods: before the intervention started; its first two years, when the Ministry of Health's scheme was in place; and subsequent years. Source: authors' calculations using Clalit Health Services data.

# A Appendix

# Additional Tables and Figures

Table A1: Difference-in-Differences Estimates: Robustness

| | Readmission | | | | |
|---|---|---|---|---|---|
| Horizon: | 30-day | | | 60-day | 90-day |
| Specification: | Baseline | Excl. 65 | Excl. 64-65 | Baseline | Baseline |
| | (1) | (2) | (3) | (4) | (5) |
| Old × After (First Two Years) | $-0.010^{***}$ | $-0.011^{***}$ | $-0.010^{**}$ | $-0.014^{***}$ | $-0.020^{***}$ |
| | (0.003) | (0.004) | (0.004) | (0.005) | (0.005) |
| Old × After (Subsequent Years) | $-0.002$ | $-0.003$ | $-0.002$ | $-0.007$ | $-0.013^{***}$ |
| | (0.004) | (0.004) | (0.004) | (0.005) | (0.005) |
| Old | $0.015^{***}$ | $0.017^{***}$ | $0.016^{***}$ | $0.025^{***}$ | $0.034^{***}$ |
| | (0.002) | (0.003) | (0.003) | (0.003) | (0.003) |
| Quarter and Hospital Dummies | Yes | Yes | Yes | Yes | Yes |
| Observations (Admissions) | 171,540 | 155,837 | 140,186 | 171,540 | 171,540 |
| Clusters (Hospitals) | 28 | 28 | 28 | 28 | 28 |
| Mean dependent variable | 0.161 | 0.161 | 0.162 | 0.224 | 0.265 |
| Model rank | 62 | 62 | 62 | 62 | 62 |
| Observations | 171,540 | 155,837 | 140,186 | 171,540 | 171,540 |
| Adjusted $R^2$ | 0.003 | 0.004 | 0.003 | 0.005 | 0.006 |

*Notes:* S.E. clustered by hospital in parentheses. $^*$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01. Difference-in-differences estimates of the impact of the intervention on hospital readmission, using different specifications. Column (1) is our main specification, shown also in Table 4. Column (2) includes controls for demographics, risk scores, and admission characteristics. Columns (3) and (4) vary the definition of age groups. In (3) Old refers to the 66–70 age groups and patients aged 65 are omitted. In (4) Young refers to the 60–63 age group and Old to the 66–70 age group, and patients aged 64–65 are omitted. Columns (5) and (6) estimate the same specification as in (1) with 60- and 90-day readmissions as the dependent variable. Source: authors' calculations using Clalit Health Services data.

Table A2: Estimates of the Intervention Impact on Index-Admission Length of Stay

| | Index-Admission Length of Stay | | | |
|---|---|---|---|---|
| | All | | High-Risk | |
| Quarter and Hospital Dummies | No | Yes | No | Yes |
| | (1) | (2) | (3) | (4) |
| Old × After (First Two Years) | 0.036 | −0.0001 | 0.362 | 0.301 |
| | (0.091) | (0.088) | (0.299) | (0.288) |
| Old × After (Subsequent Years) | 0.042 | −0.004 | 0.261 | 0.180 |
| | (0.073) | (0.066) | (0.259) | (0.265) |
| Old | 0.154*** | 0.168*** | −0.100 | −0.033 |
| | (0.054) | (0.052) | (0.201) | (0.197) |
| After (First Two Years) | 0.110 | | 0.169 | |
| | (0.094) | | (0.204) | |
| After (Subsequent Years) | 0.189 | | 0.023 | |
| | (0.124) | | (0.220) | |
| Observations (Admissions) | 171,540 | 171,540 | 19,453 | 19,453 |
| Clusters (Hospitals) | 28 | 28 | 27 | 27 |
| Mean dependent variable | 5.184 | 5.184 | 6.173 | 6.173 |
| Model rank | 6 | 62 | 6 | 57 |
| Observations | 171,540 | 171,540 | 19,453 | 19,453 |
| Adjusted $R^2$ | 0.0003 | 0.019 | 0.0003 | 0.017 |

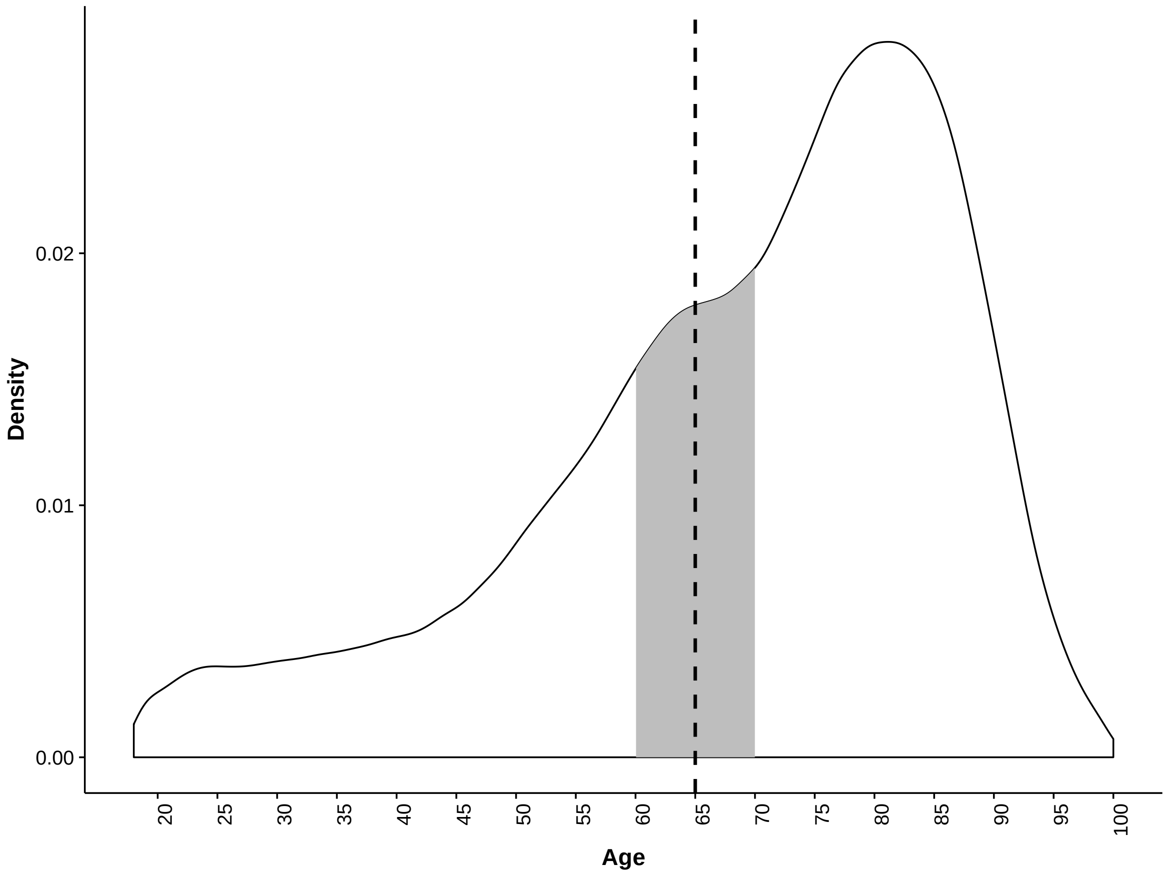
*Notes:* S.E. clustered by hospital in parentheses. $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01. Length of stay of the index admission is measured in days. Old and Young refer to patients aged 65–70 and 60–64 respectively. Before and After refer to periods before and after the beginning of the intervention, in July 2012. We further break After to two period: 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 15% of patients with the highest readmission risk, based on the PREADM model. Source: authors' calculations using Clalit Health Services data.

Table A3: Difference-in-Differences Estimates: The Intervention and One-Year Mortality

| | One-Year Mortality | | | |
|---|---|---|---|---|
| | All | | High-risk | |
| Quarter and Hospital Dummies | No | Yes | No | Yes |
| | (1) | (2) | (3) | (4) |
| Old × After (First Two Years) | $-0.012^{**}$ | $-0.013^{***}$ | $-0.036$ | $-0.039$ |
| | (0.005) | (0.005) | (0.029) | (0.029) |
| Old × After (Subsequent Years) | 0.008 | 0.006 | 0.020 | 0.016 |
| | (0.006) | (0.006) | (0.026) | (0.027) |
| Old | $0.028^{***}$ | $0.029^{***}$ | 0.015 | 0.020 |
| | (0.003) | (0.003) | (0.016) | (0.017) |
| After (First Two Years) | $0.011^{**}$ | | 0.027 | |
| | (0.005) | | (0.021) | |
| After (Subsequent Years) | 0.006 | | 0.016 | |
| | (0.005) | | (0.020) | |
| Observations (Admissions) | 149,180 | 149,180 | 16,761 | 16,761 |
| Clusters (Hospitals) | 28 | 28 | 27 | 27 |
| Mean dependent variable | 0.132 | 0.132 | 0.349 | 0.349 |
| Model rank | 6 | 58 | 6 | 53 |
| Adjusted $R^2$ | 0.002 | 0.010 | 0.001 | 0.008 |

*Notes:* S.E. clustered by hospital in parentheses. $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01. All-cause one-year mortality is mortality during 365 days from the discharge date of the index admission (throughout this study, we only consider patients alive at discharge). 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 to two period: 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 15% of patients with the highest readmission risk, based on the PREADM model. Source: authors' calculations using Clalit Health Services data.

Figure A1: Patient Age at Index Admission (study sample in gray)




*Notes:* Kernel density estimates of the distribution of patient age upon each of Clalit's covered index admission between 2009–2016. The gray band denotes the sample of 171,540 admissions of patients aged 60–70 covered in this study. Only patients aged 65 and older were targeted by the intervention and had readmission risk scores calculated for them in real time. Risk scores were not available at real time for patients aged 60–64, who serve as a retrospective comparison group. We retrospectively calculated risk scores for this group. Source: authors' calculations using Clalit Health Services data.

Figure A2: Availability of Readmission Risk Scores in Real Time


*Notes:* Risk scores were calculated every 5th of each calendar month, beginning July 2012, for all patients aged 65 years or older. The slight variation in risk scores availability each first quarter is due to rounding of age in the (original) source code used to calculate the scores. Source: authors' calculations using Clalit Health Services data.