Health Care Home: Early Evidence from Linked Administrative Data in New Zealand

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Abstract:
Our analysis presents a case study on the impacts of Health Care Home (HCH) – a large-scale technology-based healthcare innovation in New Zealand's primary healthcare system. For our analysis, we link the registered population of health practices within the Wellington region to administrative hospital admission data for quarterly periods between 2014 and 2017. By employing variation in the timing of HCH implementation across practices (selected via propensity score matching), we estimate differences-in-differences models to investigate effects of the intervention on multiple patient outcomes. Additionally, we incorporate a number of empirical specifications to test the robustness of estimates. HCH results in a statistically significant reduction in the likelihood of emergency department (ED) presentations by 6-8 percent, with no significant impacts on other health outcomes. The impact on ED presentations aligns with the expectation that the HCH intervention would produce downstream effects of a reduced economic burden on public hospital services.

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1. INTRODUCTION

The primary objective of this study is to provide a comprehensive understanding of the downstream effects (Maeng et al. 2012) of large-scale technology-based healthcare innovation models. We focus on a healthcare innovation in New Zealand's (NZ) primary healthcare system, known as the Health Care Home (HCH) initiative to investigate the impact of its implementation on a wide array of health events.

HCH in NZ is inspired from a health care innovation model developed by a Seattle (USA)-based non-profit healthcare organisation, Group Health Cooperative (GHC). In 2007, GHC implemented a pilot programme labelled the "medical home" model of primary health care services. Their approach was multidisciplinary in nature, patient-centred, and used electronic health information and data to apply a proactive philosophy to primary healthcare delivery (McCarthy et al. 2009). Pinnacle Midlands Health Network (2018) was the first NZ provider to learn from GHC's innovations in this space and established the first HCH practice in NZ (in Hamilton[1]) in 2011 (Middleton et al. 2018). Since then, HCH has been rolled out across 128 health practices across the country (Health Care Home Collaborative, 2017).

Referring to the broader international literature in this space, Grant and Greene (2012) provide a US-based descriptive overview of HCH, where the framework is described as aiming to widen the scope of primary health care and improve health care delivery. There are also a number of studies focussing on the impacts for vulnerable groups, such as individuals with complex needs, and children with difficult paediatric cases (Grant & Greene 2012; Middleton et al. 2018). However, with respect to patient outcomes downstream the scant evidence in existing literature is mixed. For instance, a few studies (Gilfillan et al. 2010; Maeng et al. 2012) find that the medical home model is associated with cumulative drops in inpatient events,

[1] In April 2011, Northcare Grandview Medical Centre (Hamilton) was the first practice to implement HCH.

readmissions and reduction in long-term health costs. On the other hand, other authors (Martsolf et al. 2012; Werner et al. 2014) find no association between this framework and patient experiences or rates of emergency department (ED) use by patients. We add to the related literature by providing an international perspective to the current US-based empirical evidence on the effectiveness of primary health care models such as HCH or medical home on patient outcomes.

To capture the downstream effects of HCH implementation, we consider a range of health events of interest such as excess length of hospital stay, incidence of acute admission, ED presentation, ambulatory sensitive hospitalisations (ASH), and readmission. Further, we employ multiple specifications to ensure robustness of findings.

2. THE HCH MODEL IN NZ

HCH is "an integrated care management model…designed to deliver an improved and more sustainable primary care service" (Health Care Home Collaborative 2019). The HCH model covers four domains: provision of urgent and unplanned care; ensuring proactive care for individuals with complex needs; enabling systematic routine and preventative care; and maximizing business efficiency.

In general, HCH is a multi-disciplinary team-based model of "whole-practice transformation" (Downs 2017). This approach offers alternatives to face-to-face consults, better triage and service targeting (using population risk stratification), more proactive care planning, utilize of a wider range of health professionals (nurses, health care assistants etc.) and lean business practices that improve the use of capital resources (technology, shared spaces etc.). Essentially, it aims to better manage the mix of acute, routine and preventative treatments by changing the input mix (e.g. staff time, practitioner tools and business activities). The HCH model adjusts the mix of staff and resources to focus more on proactive and preventative care and toward patients with more complex needs. These changes are combined with 'lean' business processes and new technology.

In 2016, the HCH National Collaborative was established in NZ by a collective of regional and national health agencies[2]. The aim of this initiative was to support ongoing establishment of HCH across NZ and ensure consistency in its adoption. In particular, this collaborative developed a set of standards and a "working framework for describing and credentialing the Health Care Home model of care" (Hefford 2018).

In our context, Compass Health, a member of the HCH collaborative, began phased HCH implementation[3] across a number of practices in the greater Wellington region in 2016. These interventions have been disseminated across 20 practices between July 2016 and April 2018.

The long-term expectations by Compass Health (2017; 2018) include better healthcare services with respect (but not limited) to: reduced use of ED and acute hospital services; meeting patients' needs without the requirement of making appointments; extended hours of medical services; incorporation of new medical professional roles such as primary health care practice assistant and nurse practitioner; higher usage of online patient portal; increased integration of modern healthcare technology, including increased usage of patient portal; and promoting community services integration.

[2] Includes several primary health organisations (PHOs), District Health Boards (DHBs) and the Royal College of General Practitioners.

[3] Practices applied to Compass Health to adopt the HCH model by submitting an Expression of Interest. The approval of HCH implementation (by Compass Health) would then be conditional on practices meeting specific criteria in accordance with the HCH collaborative standards and completion of pre-implementation phases (including a readiness, engagement and scoping the gap phase). To the best of our knowledge, conditional on a practice meeting the relevant criteria, the timing of HCH implementation is not under the directive of Compass Health.

3. DATA

Our analysis links quarterly data from the enrolled population of Compass Health practices with national hospital data from the National Minimum Dataset (NMDS)[4] for 2014 to 2017.[5] The initial sample is 342,136 individuals registered in 58 Compass practices. For the purpose of our analysis, we apply a few criteria to the population of interest.

To ensure comparability across the treated and control practices, we exclude all individuals who switched across or dropped out of enrolled practices to reduce confounding. We further remove observations with missing demographic information. Finally, we apply a propensity score matching method (following Khandker et al. 2009) to select a comparable group of non-HCH practices for the treatment group based on the registered population's characteristics.[6]

More specifically, by regressing the treatment indicator (using logistic regression) on the pre-intervention proportions of socio-demographic characteristics (age, sex, ethnicity and deprivation index) associated with each practice, we generate propensity scores (Becker & Ichino 2002). The logistic regression-generated propensity scores represent the likelihood of a practice receiving the HCH intervention conditional on the socio-demographic characteristics of the population they serve. Identification of the matched sample relies on satisfying a 'balancing property' that ensures HCH intervention is orthogonal to the covariates conditional on the propensity scores. Next, the practices are stratified into seven 'blocks' generated such that within each block the HCH and non-HCH practices on average have the same propensity scores (Becker & Ichino 2002). Practices with missing blocks are excluded from the sample.[7]

[4] The NMDS is not a publicly available data. Access to the NMDS information requires Ministry of Health (NZ)'s approval.
[5] To provide a NZ-specific perspective, 93 percent of the country's population are enrolled in a primary health organization as of July 2018 (accessed from Ministry of Health NZ, 2018).
[6] For robustness purposes we also perform our analysis utilising the full sample prior to application of the propensity score matching. The findings of this robustness exercise are provided in Appendix Table A.2.
[7] We further check our results with the broader sample prior to selecting matched practices using propensity scores. The results are qualitatively similar to our main analysis.

The resultant sample consists of 2,698,283 observations (individual-practice-quarter level) representing 203,570 individuals from 45 practices. We classify the sample by number of individuals in practice-quarter cells in Appendix Table A.1 along with the implementation dates for the HCH practices. Our sample includes six practices that implemented HCH in our study timeframe, such that there is a minimum of one (and maximum of five) quarter(s) post-implementation. The remaining 39 practices did not implement HCH during the study period.

We utilize the NMDS to construct indicators for excess length of stays; acute admissions; ED presentations; ASH events and; readmissions. These health event outcomes are consistent with the relevant literature (e.g. see Gilfillan et al. 2010; Larson & Reid 2010; Rosenberg et al. 2012). Additionally, we also include frequency (i.e. intensity) of the aforementioned health events by individual-practice-quarter. The specific definition of each outcome of interest are provided in Table 1 and the associated descriptives in Table 2.

Given the long-term objectives underlying HCH implementation, it is expected that an effective intervention would result in reduced incidence of the above health events over time, (through efficient and improved health care services, such as virtual consultations and upgraded medical support), relative to non-HCH practices.

< Insert Table 1 and 2 about here >

4. IDENTIFICATION STRATEGY

We exploit variation in assignment and timing of HCH implementation across practices in a difference-in-differences (DID) framework. At the practice-quarter level, we estimate four empirical models ranging from a baseline to more saturated specifications. In the baseline regression (Model 1), we regress the health events on HCH implementation by controlling for quarter (accounting for time) and practice fixed effects. Model 1 is:

$$Y_{ipt} = \alpha_0 + \alpha_1 HCH_{pt} + \gamma_p + \lambda_t + v_{ipt} \qquad (1)$$

where Y_{ipt} is a health event of individual *I* registered in practice p at time t (given by quarter of a year). HCH_{pt} is a dichotomous indicator of HCH implementation based on timing of the intervention. Time fixed effects λ_t account for time-specific factors that may affect all practices as well the outcomes of interest. γ_p represents practice-specific fixed effects that incorporate time-invariant unobserved variables specific to each practice. v_{ipt} represents the error term. Importantly, α_1 estimates the association between HCH intervention and the health events of interest.

In Model 2, we add socio-demographic controls including age, sex, ethnicity and socio-economic deprivation index (measured in quintiles). Table 3 presents descriptive information of the individual-level variables.

Next, we include practice-specific linear time trends (Angrist & Pischke 2013) to account for unobserved practice-related heterogeneities that evolve linearly over time. Model 3 is:

$$Y_{ipt} = \delta_0 + \delta_1 HCH_{pt} + \delta_2' X_{ipt} + \gamma_p + \lambda_t + \Omega_s t + e_{ipt} \quad (2)$$

where X_{ipt} is a vector of individual-level characteristics. The reference groups are male, 80 years and above, other ethnicity, and highest socio-economic deprivation. Variable $\Omega_s t$ represents practice-specific linear time trend and δ_1 estimates the relationship between HCH implementation and health outcomes.

Finally, in Model 4, we perform a parameterized event study to control for anticipatory and post-treatment effects of HCH intervention (Autor 2003). Model 4 is:

$$Y_{ipt} = \rho_0 + \rho_1 HCH_{pt} + \rho_2' X_{ipt} + \theta_1 \delta_{st} + \theta_2 (\delta_{st} * HCH_{pt}) + \gamma_p + \lambda_t + \epsilon_{ipt} \quad (3)$$

where δ_{st} is a pre-treatment trend that measures distance of particular quarter t relative to time of HCH implementation. More specifically, δ_{st} equals 0 for all non-HCH practices and for HCH practices at time of implementation, negative for the pre-treatment and positive for postintervention period representing the relative distance from the intervention quarter. We further include an interaction between the pre-treatment trend and HCH implementation indicator ($\delta_{st} * HCH_{pt}$). Therefore, θ_1 estimates the pre-implementation trend in the health outcomes of interest, while θ_2 identifies the difference in health events before and after HCH implementation. If θ_1 is statistically significant, policy endogeneity may be present.

We estimate probit models for the binary health indicators and ordinary least squares regressions for the frequency of the health outcomes. The standard errors are corrected for clustering at the practice-level.

In an additional specification (Model 5), we estimate linear fixed effects regressions to account for individual-specific time-invariant characteristics that may affect the relationship of research interest.

< Insert Table 3 about here >

5. RESULTS

We report our DID estimates for the binary health indicators in Table 4. With respect to the baseline models (Models 1 and 2), only for ED presentation indicator, we find statistically significant regression coefficients (column 3).

The negative relationship between HCH implementation and ED presentations holds across the more saturated models as well. In Models 3-5, the marginal effects remain closely similar to our baseline regression estimates. Interpreting the regression estimates as a proportion of the respective sample mean, the marginal effects for ED presentations in Model 3 translates to an average 6.9 percent drop in the probability (marginal effect / sample mean = 0.00104 / 0.015). Focusing on Model 4, the absolute proportion rises marginally, representing a decline in the probability of ED presentations by 8.4 percent (0.00126 / 0.015) on average. Model 5 yields qualitatively similar results. The significant negative relationship between HCH and incidence of ED presentations is consistent with the existing evidence in the current literature (Grumbach & Grundy 2010; Compass Health 2017[b]; Ernst & Young 2018). Further, the drop in the likelihood of ED presentations indicate that the observed impact of HCH meets with one of the long-term overarching objectives of the model.

Importantly in Model 4, referring to the marginal effects of the pre-treatment trend (across the health indicators), we do not observe any statistically significant variation in the health outcomes of interest during the prior periods leading up to the HCH intervention. Therefore, no strong evidence of policy endogeneity.

In Table 5, we re-estimate all five specifications for the intensity of the respective health events. For the most part, we do not find any significant association between HCH implementation and the dependent variables (bar frequency of ED presentations). Consistent with findings from Table 4, in the more saturated models (Models 3 and 4), we find statistically significant relationships between HCH implementation and frequency of ED presentations.

< Insert Table 4 and 5 about here >

6. PUBLIC HEALTH IMPLICATIONS

A major advantage of this study is the use of administrative data, which permits a population-based perspective. Despite the fact that our focus is region-focussed, the empirical evidence has important implications from the public health perspective especially with respect to implementation of policies such as the Affordable Care Act in the U.S., which is expected to increase demand for ED services, placing greater pressure on public hospital resources (McClelland et al. 2014).

Given the timing of the healthcare intervention, our analysis presents a short-term impact of HCH. It is important to note that the statistically insignificant effects observed across the majority of health events possibly indicate that the expected health benefits of HCH may not be realized within a limited time span succeeding HCH implementation due to potentially high adjustment costs for healthcare service users (and providers) to HCH implementation in the short term. Future analysis should aim to assess long-term outcomes (once more data becomes available) across a greater range of indicators – so that the immediate impacts at the practice level can also be subject to empirical investigation.

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Table 1
Health events considered in our analysis

Health outcome	Definition and construction of indicator variable	Intensity
Excess length of stay	Episode-specific binary indicator for whether an individual's length of stay exceeded diagnosis-related group-specific mean	Number of excess length of stay[8]
Acute admission	Binary indicator for whether an individual has a health episode classified as an acute admission. This includes mental health- related acute admissions. Derived from 'Admission Type' information in the NMDS.	Number of acute admissions.
ED presentation	Binary indicator for whether an individual has an emergency hospital admission. Derived from 'Episode Type' information in NMDS.	Number of ED events.
Ambulatory Sensitive Hospitalisation (ASH)	Binary indicator for whether an individual has an admission that is considered potentially reducible "resulting from a prophylactic or therapeutic interventions deliverable in a primary care setting" (Jackson & Tobias 2001). A detailed list of ASH conditions is provided and updated by the Ministry of Health (2018). This variable is constructed using the principal diagnosis information.	Number of ASH events.
Readmission	Binary indicator for whether an individual was readmitted in hospital for an acute condition within 30 days of the previous admission.[9]	Number of readmissions.

Notes: All individual-level health indicators are defined by practice-quarter.

[8]The indicator for excess length of stay is based on a measure that takes positive values when the observed length of stay exceeds the diagnosis-related group-specific mean and negative for the reverse. Our indicator equals 1 when the measure is positive and 0 otherwise (Zhan & Miller 2003; Mutter et al. 2008; Jiang & Pacheco 2014).

[9] The Ministry of Health considers the threshold of 28 days for readmissions. However, maintaining consistency with the international literature, we construct our readmission using the 30-day threshold (Amarasingham et al. 2010; Mc.Hugh et al. 2013). Considering 28-day readmissions does not affect our regression estimates.

Table 2
Descriptive statistics of health outcomes

	Overall sample	Non-HCH practices	HCH practices	p-value of difference
	Proportion: μ	Proportion: μ_n	Proportion: μ_h [mean at t=0; mean at t=1]	(μ_n- μ_h)
Excess length of stay (indicator)✓	1.060%	1.015%	1.110% [1.086; 1.234]	0.000
Frequency of excess length of stay	0.012	0.011	0.012 [0.012; 0.014]	0.000
Acute admission✓	1.618%	1.590%	1.648% [1.596; 1.924]	0.000
Frequency of acute admissions	0.019	0.019	0.020 [0.019; 0.023]	0.000
ED presentations✓	1.398%	1.412%	1.382% [1.333; 1.641]	0.034
Frequency of ED presentations	0.015	0.016	0.015 [0.014; 0.018]	0.000
ASH event✓	0.566%	0.552%	0.581% [0.564; 0.673]	0.000
Frequency of ASH events	0.006	0.006	0.006 [0.006; 0.007]	0.000
Readmission✓	0.187%	0.185%	0.190% [0.183; 0.227]	0.006
Frequency of readmissions	0.003	0.002	0.003 [0.002; 0.003]	0.012
Observations	2,698,283	1,425,140	1,273,143	

Notes: Each observation is at the individual-practice-quarter level except for consultations/registrations, which are estimated at the practice-quarter level.
✓Variables are binary indicators and the means for these variables are presented in percentage terms.

Table 3
Descriptive statistics of individuals registered in Compass health practices

	Overall sample	Non-HCH practices	HCH practices	p-value of difference
	Proportion: μ (%)	Proportion: μn (%)	Proportion: μh (%)	(μn- μh)
Sex				
Female	52.31	52.61	51.97	0.00
Male (reference)	47.69	47.39	48.03	0.00
Age				
Under 10 years	12.91	11.99	13.94	0.00
10-19 years	12.04	11.72	12.40	0.00
20-29 years	9.83	9.97	9.68	0.00
30-39 years	12.47	12.86	12.05	0.00
40-49 years	16.37	16.92	15.76	0.00
50-59 years	15.57	16.26	14.80	0.00
60-69 years	11.23	11.46	10.97	0.00
70-79 years	6.61	6.18	7.10	0.00
80 years and above (reference)	2.97	2.66	3.32	0.00
Ethnicity				
European	71.98	73.55	70.22	0.00
Māori	8.90	7.91	10.00	0.00
Pacific Peoples	4.91	5.09	4.72	0.00
Asian	10.35	10.09	10.65	0.00
MELAA	1.06	0.98	1.15	0.00
Others (reference)	2.34	1.97	2.76	0.00
Socio-economic deprivation: Quintile				
1- Lowest deprivation	36.44	37.20	35.58	0.00
2	24.43	23.54	25.42	0.00
3	18.37	17.48	19.37	0.00
4	12.59	12.79	12.37	0.00
5- Highest deprivation (reference)	8.17	8.99	7.26	0.00
Observations	2,698,283	1,425,140	1,273,143	

Table 4
Difference-in-differences model with binary health events using practices selected from propensity score matching

	Dependent variables (binary indicator of health events)				
	Excess stay	Acute admission	ED presentation	ASH event	Readmission
Sample mean	0.011	0.017	0.015	0.006	0.002
Model 1: Time and practice-specific fixed effects					
HCH implementation	-0.00039*	-0.00022	-0.00112**	-0.00027	-0.00012
	(0.00023)	(0.00032)	(0.00047)	(0.00029)	(0.00017)
Model 2: Model 1 + demographic controls (age, sex, ethnicity, quintile)					
HCH implementation	-0.00036	-0.00017	-0.00110**	-0.00025	-0.00010
	(0.00023)	(0.00033)	(0.00049)	(0.00030)	(0.00016)
Model 3: Model 2 + practice-specific linear time trends					
HCH implementation	-0.00020	0.00005	-0.00104***	-0.00004	0.00009
	(0.00031)	(0.00037)	(0.00029)	(0.00020)	(0.00028)
Model 4: Model 2 + event study					
HCH implementation	-0.00025	0.00001	-0.00126***	-0.00031	-0.00009
	(0.00029)	(0.00033)	(0.00036)	(0.00058)	(0.00023)
Pre-treatment (δ_{pt})	-0.00000	0.00005	0.00003	0.00007	0.00004
	(0.00004)	(0.00005)	(0.00004)	(0.00008)	(0.00003)
δ_{pt}X HCH implementation	-0.00006	-0.00029*	0.00004	-0.00028	-0.00023**
	(0.00014)	(0.00016)	(0.00017)	(0.00018)	(0.00010)
Observations	2,552,113	2,552,113	2,403,629	2,552,113	2,552,113
Model 5: Individual fixed effects regression					
HCH implementation	-0.00037	-0.00016	-0.00092*	-0.00025	-0.00011
	(0.00024)	(0.00036)	(0.00052)	(0.00026)	(0.00018)
Observations			2,698,283		
No. of individuals			203,570		

Notes: We perform the propensity score matching on the practices by aggregating the observable socio-demographic variables at the practice-level for the whole of pre-implementation period (defined by the period 2014 third quarter-2016 second quarter). The marginal effects from probit regressions using all the matched practices along with the respective standard errors (in parentheses) are reported in the above table. The standard errors are corrected for clustering at the practice-level. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels respectively. We estimate probit regressions for Model 1-4 and linear fixed effects regressions for Model 5.

Table 5
Difference-in-differences model with intensity of health events using practices selected from propensity score matching

	Dependent variables (intensity of health events)				
	Number of excess stays	Number of acute admissions	Number of ED presentation	Number of ASH events	Number of readmissions
Sample mean	0.012	0.019	0.015	0.006	0.002
Model 1: Time and practice-specific fixed effects					
HCH implementation	-0.00051 (0.00032)	-0.00037 (0.00065)	-0.00091 (0.00070)	-0.00035 (0.00036)	-0.00018 (0.00029)
Model 2: Model 1 + demographic controls (age, sex, ethnicity, quintile)					
HCH implementation	-0.00047 (0.00032)	-0.00029 (0.00062)	-0.00088 (0.00072)	-0.00035 (0.00036)	-0.00016 (0.00028)
Model 3: Model 2 + practice-specific linear time trends					
HCH implementation	-0.00093* (0.00052)	-0.00076 (0.00075)	-0.00177*** (0.00063)	-0.00040 (0.00035)	-0.00024 (0.00050)
Model 4: Model 2 + event study					
HCH implementation	-0.00062 (0.00051)	-0.00012 (0.00071)	-0.00098** (0.00044)	-0.00013 (0.00033)	-0.00014 (0.00043)
Pre-treatment (δ_{pt})	0.00006 (0.00005)	0.00011 (0.00009)	-0.00003 (0.00013)	0.00005 (0.00004)	0.00003 (0.00002)
δ_{pt}X HCH implementation	-0.00011 (0.00021)	-0.00045* (0.00025)	0.00015 (0.00025)	-0.00031** (0.00012)	-0.00010 (0.00011)
Model 5: Individual fixed effects regression					
HCH implementation	-0.00062** (0.00029)	-0.00037 (0.00050)	-0.00096 (0.00065)	-0.00039 (0.00029)	-0.00016 (0.00027)
Observations			2,698,283		
No. of individuals			203,570		

Notes: The estimated coefficients and standard errors (in parentheses) from OLS (and linear fixed effects for Model 5) regressions based on matched practices are reported in the above table. The standard errors are corrected for clustering at the practice-level. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels respectively.

Appendix

Table A.1 - Number of registered individuals per practice-quarter

		2014 Quarters				2015 Quarters				2016 Quarters				2017 Quarters			
HCH implementation quarter	Practice	1st	2nd	3rd	4th	1st	2nd	3rd	4th	1st	2nd	3rd	4th	1st	2nd	3rd	4th
	1	1,773	1,781	1,803	1,822	1,829	1,835	1,864	1,874	1,888	1,893	1,924	1,947	1,968	1,995	2,040	2,079
2016q3	2	8,302	8,488	8,641	8,841	9,005	9,183	9,360	9,609	9,805	9,975	10,244	10,471	10,742	10,987	11,257	11,645
	3	1,403	1,428	1,472	1,507	1,537	1,557	1,594	1,622	1,696	1,683	1,750	1,792	1,864	1,925	2,004	2,104
	4	373	387	395	412	420	429	442	457	462	471	476	490	514	531	549	587
	5	2,567	2,607	2,646	2,700	2,732	2,769	2,833	2,847	2,901	2,946	3,001	3,077	3,159	3,240	3,316	3,414
2017q4	6	3,201	3,246	3,305	3,370	3,442	3,541	3,650	3,727	3,863	3,947	4,073	4,212	4,355	4,503	4,659	4,850
2016q4	7	1,759	1,808	1,826	1,843	1,867	1,911	1,952	1,985	2,023	2,044	2,108	2,136	2,205	2,257	2,287	2,357
	8	6,584	6,726	6,872	7,066	7,287	7,436	7,632	7,797	7,976	8,136	8,430	8,638	8,860	9,090	9,333	9,683
	9	693	713	724	732	757	767	784	799	811	830	849	860	877	901	923	954
2017q3	10	5,737	5,844	5,974	6,121	6,237	6,390	6,553	6,703	6,953	7,153	7,406	7,633	7,815	8,112	8,350	8,673
	11	855	880	892	921	952	972	1,001	1,043	1,070	1,115	1,152	1,177	1,218	1,279	1,353	1,421
	12	641	651	665	681	725	756	799	829	847	881	910	939	971	996	1,025	1,056
2018q2	13	1,892	1,922	1,975	2,032	2,105	2,179	2,296	2,408	2,556	2,661	2,847	2,977	3,154	3,322	3,485	3,666
	14	2,056	2,086	2,116	2,145	2,161	2,190	2,237	2,281	2,308	2,330	2,386	2,411	2,440	2,485	2,535	2,609
	15	3,796	3,822	3,887	3,981	4,073	4,138	4,191	4,211	4,273	4,340	4,367	4,384	4,441	4,522	4,561	4,656
	16	2,489	2,532	2,558	2,623	2,654	2,679	2,723	2,754	2,789	2,831	2,857	2,913	2,962	3,020	3,107	3,185
2017q4	17	7,005	7,114	7,236	7,355	7,481	7,599	7,705	8,068	8,196	8,338	8,486	8,612	8,779	9,009	9,198	9,344
2018q1	18	6,326	6,381	6,447	6,568	6,644	6,714	6,807	6,879	6,976	7,086	7,188	7,260	7,347	7,458	7,590	7,720
2017q4	19															5,360	5,509
	20	373	381	382	387	401	410	418	433	437	438	441	453	468	485	497	501
	21	2,603	2,654	2,699	2,749	2,781	2,862	2,910	2,961	3,038	3,124	3,202	3,299	3,398	3,486	3,582	3,712
	22	1,850	1,883	1,886	1,907	1,919	1,956	1,972	1,995	2,015	2,028	2,060	2,079	2,093	2,111	2,144	2,180
	23	4,683	4,729	4,801	4,891	5,004	5,148	5,270	5,427	5,589	5,691	5,940	6,119	6,379	6,628	6,814	7,056
	24	3,522	3,569	3,636	3,691	3,723	3,767	3,813	3,890	3,929	3,977	3,993	4,087	4,164	4,285	4,348	4,429
	25	5,031	5,116	5,190	5,283	5,378	5,468	5,567	5,662	5,750	5,849	6,005	6,116	6,230	6,398	6,531	6,698
	26	3,539	3,600	3,631	3,657	3,688	3,744	3,813	3,862	4,006	4,093	4,211	4,323	4,421	4,608	4,723	4,902
2017q3	27	8,146	8,248	8,353	8,463	8,639	8,756	8,871	8,938	9,048	9,167	9,336	9,454	9,596	9,813	10,002	10,207
2018q1	28	1,598	1,616	1,634	1,649	1,666	1,684	1,701	1,712	1,733	1,756	1,782	1,817	1,860	1,903	1,932	1,991
	29	1,248	1,261	1,281	1,298	1,305	1,348	1,386	1,420	1,442	1,466	1,490	1,503	1,513	1,544	1,582	1,607
2018q3	30	4,600	4,655	4,724	4,798	4,863	4,924	5,093	5,157	5,220	5,310	5,404	5,507	5,615	5,734	5,850	5,988

Table A.1 (continued): Number of registered individuals per practice-quarter

		2014 Quarters				2015 Quarters				2016 Quarters				2017 Quarters			
HCH implementation quarter	Practice	1st	2nd	3rd	4th	1st	2nd	3rd	4th	1st	2nd	3rd	4th	1st	2nd	3rd	4th
	31	1,609	1,631	1,672	1,704	1,721	1,741	1,763	1,770	1,774	1,780	1,807	1,830	1,855	1,864	1,886	1,913
	32	6,626	6,731	6,817	6,903	7,011	7,098	7,170	7,257	7,332	7,463	7,585	7,699	7,828	7,969	8,122	8,293
	33	4,232	4,366	4,409	4,490	4,552	4,622	4,712	4,776	4,869	4,962	5,043	5,103	5,203	5,321	5,462	5,586
	34	1,874	1,883	1,919	1,965	1,991	2,036	2,140	2,172	2,239	2,245	2,307	2,354	2,394	2,468	2,506	2,574
2016q3	35	2,198	2,240	2,301	2,327	2,362	2,372	2,401	2,426	2,474	2,508	2,548	2,597	2,631	2,680	2,745	2,822
	36	2,251	2,276	2,298	2,322	2,364	2,413	2,481	2,542	2,592	2,641	2,703	2,750	2,816	2,868	2,933	3,012
	37	3,074	3,113	3,135	3,169	3,199	3,229	3,253	3,273	3,319	3,345	3,418	3,491	3,543	3,600	3,650	3,731
	38	5,584	5,641	5,734	5,853	5,948	6,060	6,147	6,259	6,373	6,481	6,641	6,751	6,873	7,052	7,231	7,440
	39	4,417	4,451	4,517	4,598	4,718	4,770	4,866	4,985	5,072	5,180	5,305	5,421	5,522	5,653	5,811	5,943
2017q4	40	3,137	3,204	3,252	3,336	3,417	3,475	3,513	3,542	3,598	3,634	3,768	3,826	3,890	3,950	4,028	4,148
	41	269	278	276	286	283	295	313	331	344	351	360	373	387	411	431	452
	42	1,576	1,623	1,668	1,728	1,750	1,774	1,816	1,851	1,876	1,912	1,958	1,992	2,032	2,090	2,152	2,289
2018q1	43	4,143	4,201	4,258	4,292	4,328	4,371	4,443	4,469	4,549	4,623	4,712	4,771	4,872	4,965	5,054	5,173
2018q2	44	3,859	3,967	4,055	4,131	4,172	4,255	4,363	4,435	4,508	4,596	4,659	4,734	4,842	4,955	5,066	5,231
2016q3	45	6,676	6,751	6,805	6,860	6,939	7,063	7,176	7,281	7,413	7,501	7,618	7,720	7,870	8,063	8,257	8,452

Notes: The practice identifiers marked in red implemented the health care homes model.

Table A.2: Difference-in-differences model with binary health events using all practices

	Dependent variables (binary indicator of health events)				
	Excess stay	Acute admission	ED admission	ASH event	Readmission
Sample mean	0.011	0.017	0.015	0.006	0.002
Model 1: Time and practice-specific fixed effects					
HCH implementation	-0.00035	-0.00013	-0.00120**	-0.00024	-0.00010
	(0.00022)	(0.00032)	(0.00048)	(0.00028)	(0.00020)
Model 2: Model 1 + demographic controls (age, sex, ethnicity, quintile)					
HCH implementation	-0.00033	-0.00010	-0.00118**	-0.00023	-0.00009
	(0.00023)	(0.00032)	(0.00050)	(0.00029)	(0.00016)
Model 3: Model 2 + practice-specific linear time trends					
HCH implementation	-0.00018	0.00011	-0.00111***	-0.00002	0.00011
	(0.00030)	(0.00034)	(0.00033)	(0.00018)	(0.00027)
Model 4: Model 2 + event study					
HCH implementation	-0.00028	0.00002	-0.00135***	-0.00011	-0.00003
	(0.00029)	(0.00031)	(0.00038)	(0.00023)	(0.00022)
Pre-treatment (δ_{pt})	0.00000	0.00006	0.00003	0.00004	0.00001
	(0.00004)	(0.00005)	(0.00005)	(0.00003)	(0.00002)
δ_{pt}X HCH implementation	-0.00004	-0.00027*	0.00001	-0.00021**	-0.00008
	(0.00014)	(0.00016)	(0.00017)	(0.00010)	(0.00006)
Observations	2,819,751	2,819,751	2,659,260	2,819,751	2,819,751
Individuals			235,457		

Notes: The marginal effects from probit regressions using all the matched practices along with the respective standard errors (in parentheses) are reported in the above table. The standard errors are corrected for clustering at the practice-level. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels respectively. We estimate probit regressions for Model 1-4