Health Care Homes:
Early Evidence in Wellington

October 2018

Authors: Kabir Dasgupta and Gail Pacheco

HealthCare Homes: Early Evidence in Wellington

Date: September 2018

Authors: Kabir Dasgupta and Gail Pacheco (AUT)

JEL classification: I10; I18; O35

Acknowledgements: We are grateful to a number of individuals from Compass Health and Capital & Coast District Health Board for providing the data for this study, as well as valuable contextual information. Thanks are also necessary for the team at the New Zealand Productivity Commission for providing review comments throughout the research process. Any errors or omissions remain the responsibility of the authors.

The Commission – an independent Crown entity – completes in depth inquiry reports on topics selected by the Government, carries out productivity related research and promotes understanding of productivity issues. The Commission aims to provide insightful, well-formed and accessible advice that leads to the best possible improvement in the wellbeing of New Zealanders. The New Zealand Productivity Commission Act 2010 guides and binds the Commission.

Information on the Productivity Commission can be found on www.productivity.govt.nz or by contacting +64 4 903 5150.

The NZ Work Research Institute (NZWRI) at AUT provides high quality research across a broad multidisciplinary programme concerned with people and work.

More information about the NZWRI can be found at www.workresearch.aut.ac.nz.

1. Executive Summary

This paper presents a case study analysis of innovation in one part of the New Zealand (NZ) healthcare system. We focus on the NZ Health Care Home (HCH) initiative and investigate the impact of its implementation (in a large primary health organisation in NZ - Compass Health) on a wide array of health events.

HCH in NZ is adapted 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 "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, Mueller, & Tillman, 2009; Reid et al. 2010). Pinnacle Midlands Health Network[1] was the first health care organisation in NZ to learn from GHC's innovations in this space. They established the first HCH practices in NZ in 2011 (Pinnacle Midlands Health Network, n.d.; Middleton, Dunn, O'Loughlin, & Cumming, 2018). Since then, the HCH model has been rolled out across 128 health practices in the country (Health Care Home Collaborative, 2017). In addition, 12 NZ health practices from four primary health organisations (Northland District Health Board, Pinnacle, Compass Health, and ProCare) were officially certified as HCH for the first time in early 2018[2].

The HCH model is based on four international trends in primary health care. Hefford (2017) indicates these are: (i) an upsurge of interest in primary healthcare; (ii) undertaking 'lean' quality improvement theory in the health sector; (iii) increasing adoption of technology to improve the service to the patient; and (iv) co-ordinated care for individuals who have complex needs.

The existing international literature regarding the impact of primary health care initiatives such as HCH relies primarily on evidence drawn from US-based experiences. For example, Grant & Greene (2012) provide a descriptive overview of the HCH model endorsed in 2010 by the American Public Health Association. The framework is described as aiming to widen the scope of primary health care and enhancing health care delivery to users. Further, Reid et al. (2010) find that GHC's medical home model is associated with improvements in patient experiences and reduction in emergency events and hospitalizations. A few additional US-based studies including Maeng et al. (2012) and Gilfillan et al. (2010) observe that advances in primary care services (such as the medical home model) result in cumulative drops in inpatient events, readmissions and reduction in long-term health costs. In the NZ context, empirical evidence on the effectiveness of the HCH model is primarily descriptive in nature with an analysis of trends in different health outcomes (Ernst & Young, 2017; Compass Health, 2017). The analysis in the most recent study in this space (Ernst & Young, 2018) was based on a matched open cohort and multiple logistic modelling. That study design while not causal in nature did suggest that

[1] See more information at http://www.healthcarehome.co.nz/model-overview/
[2] See more information http://www.healthcarehome.org.nz/News.

the HCH model was associated with significantly lower ambulatory sensitive hospitalisations (ASH) and emergency department (ED) presentations.

Our study adds to the evidence base by conducting a comprehensive empirical analysis using difference-in-differences regression models to evaluate the impact of HCH implementation under Compass Health in Wellington, on a range of health-related events. In comparison to the existing literature, our study design accounts for omitted variable biases by incorporating practice-specific linear time trends that captures practice-related unobserved heterogeneities that may evolve linearly over time. Further, we also perform a parameterized event study to account for policy endogeneity that may result from anticipatory effects of policy implementation.

We employ large-scale quarterly data on the registered population enrolled in 55 Compass Health practices across the Wellington region over the period 2014 through 2017 (inclusive). Our analysis combines practice level information from Compass Health with hospital event information from the National Minimum Dataset (NMDS). In particular, we employ difference-in-differences regression models (and a matching process for robustness) to study the impact of HCH implementation, which was introduced during the period covered by the data at 11 practices out of the 55.

Health events of interest include the average cost associated with a hospital event (inpatient / emergency), as well as both the incidence and frequency of several hospital events such as acute admission, excess length of hospital stay, ED admission, ASH event, and risk of readmission. A secondary analysis is also conducted to focus on one health event indicator at the practice-level, the number of doctor (nurse) consultations.

In general, we find significant impacts on only one hospital-related event and this is robust across a range of specifications trialled. More specifically, we observe a statistically significant drop in ED admissions post-implementation of HCH across Compass' practices. This finding aligns with the expectation that the HCH model would reduce the use of hospital services. However, we did not find significant impacts on other hospital events such as acute admissions or risk of readmissions. These, along with the full list of health events under analysis in this study warrant future investigation at a later date to assess the long-term impacts of HCH. This study has focussed primarily on short-term impacts based on HCH timelines that mean the maximum time period of available data is five quarters post-implementation[3].

The remainder of this study is structured as follows: Section 2 provides background and context regarding the HCH model in NZ; Section 3 describes the two forms of data we merge and utilise, at the practice and hospital level; The difference-in-differences methodology is briefly portrayed in Section 4, accompanied by information on the range of specifications we trial, and robustness measures undertaken; Section 5 then provides key results and interpretations, while the section following that concludes.

[3] See Appendix A for full details on number of quarters of available data post-implementation by practice id.

2. Background on Health Care Homes

Health Care Homes (HCH) is a primary care led initiative designed to “deliver a better patient and staff experience, improved quality of care, and greater efficiency” (Health Care Home Collaborative, 2017, p. 3). 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 (see full details in Health Care Home Collaborative, 2017).

HCH is a multi-disciplinary team-based model of “whole-practice transformation” (Downs, 2017, p.46). This approach offers alternatives to face-to-face consults, better triage and service targeting (using population risk stratification), more proactive care planning, use 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 on patients with more complex needs. These changes are combined with ‘lean’ business processes and new technology. The HCH model in NZ now uses a set of standards and criteria that was developed by the HCH collaborative network in 2016.

As indicated earlier, HCH was adapted by Pinnacle Midlands Health Network (PMHN), from a model used by GHC in the United States. It was first implemented in Northcare Grandview Road Medical Centre in Hamilton in April 2011. The HCH collaborative, established by a collective of parties including several primary health organisations (PHOs), District Health Boards (DHBs) and the Royal College of General Practitioners, later developed a set of standards and model of care requirements that formed a “working framework for describing and credentialing the Health Care Home model of care” (Hefford, 2017, p. 232). This framework allows the model to be implemented in different ways, by different practices and in different regions, to reflect local priorities.

The Capital & Coast District Health Board (CCDHB) and Compass Health PHO are members of the HCH collaborative and are working together with other local PHOs (and other health care providers) to gradually implement HCH through a phased enrolment of practices across the greater Wellington region. This process commenced in July 2016, and the HCH model has now been launched in 20 Wellington health practices thus far. These interventions have been disseminated across three tranches (Compass Health, 2017a). Seven practices in Tranche 1 in July and October 2016, 13 practices in Tranche 2 between July 2017 and April 2018, with Tranche 3 yet to be implemented in late 2018.

According to Compass Health's 2017 annual report (also see Compass Health, 2018), the long-term expectations post-HCH implementation include better healthcare services with respect to:

- reduced use of ED and acute hospital services;
- meeting patients' needs without the requirement of making appointments;
- extending hours of medical services;
- incorporating new roles in medical professions (primary health care practice assistant and nurse practitioners);
- providing proactive care planning;
- increasing the usage of patient portal;
- promoting community services integration through collaborative efforts of medical experts from general practice and community service teams;
- encouraging innovative thinking such as process mapping, problem solving practices; and
- integrating modern technology in healthcare.

3. Data

The empirical analysis in this study links the enrolled (or registered) population of 55 Compass Health practices with NMDS data that records inpatient/ emergency episodes at the individual-practice-quarter level for the period 2014 to 2017. For the purpose of our analysis, we have applied several criteria to the population sample of enrolled individuals provided by Compass Health.

The initial sample of the registered population included a total of 342,136 individuals registered in 58 Compass practices. From this sample, we excluded all individuals who switched across practices over our period of interest. Second, we dropped individuals who drop out of a health practice before the end of our study period. The main reason for these exclusions is to reduce omitted variable biases that may arise from unobserved individual specific heterogeneities (such as personal reasons for relocation or switching practices). As our identification relies on comparing the pre- and post-intervention outcomes between a treatment group (practices that receive HCH) and a control (non-HCH practices) group, we apply these conditions to reduce potential biases in our regression estimates of interest. We also removed all observations with missing demographic information. As a final restriction we dropped from our sample three practices, whose data was not available in quarter 4 of 2017.

The resultant sample from the above steps contains 2,977,682 observations (at the individual-practice-quarter level) representing 235,485 individuals from 55 practices. For a better understanding of the context of our data, we report the number of individuals in per practice-quarter cells in Appendix A along with the HCH implementation dates for the practices that incorporated the health care intervention. Our sample includes 11 practices that implemented HCH during our study timeframe. This means that across the practices in the study there is a minimum of one (and maximum of five) quarters post-implementation. The remaining 45 practices did not implement HCH prior to quarter 4 of 2017.

Data on the health events of interest are derived from the NMDS (which contains administrative information on individuals' hospital events). In particular, using NMDS, we construct indicators for excess length of stays; acute admissions; ED admissions; ASH events; and readmissions. In addition, we also look at the frequency (i.e. intensity) of the aforementioned health events and change in average cost per health event (by individual-practice-quarter). Further details on the specific definition of all variables of interest are provided in Table 1 below. Given the long-term objectives underlying the HCH model, it is expected that it would result in the reduction in the 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 practices that have not implemented HCH.

Table 1: Health events considered in the analysis

Health outcome	Definition and construction of indicator variable	Intensity
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 admission	Binary indicator for whether an individual has an emergency department presentation. Derived from 'Episode Type' information in NMDS.	Number of emergency 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" (p. 212, Jackson & Tobias 2001). A detailed list of ASH conditions is provided and updated by the Ministry of Health[4]. 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[5].	Number of readmissions.
Excess length of stay	Episode-specific binary indicator for whether an individual's length of stay exceeded diagnosis-related group-specific mean	Excess duration of stay (in days)[6]
Average cost	Average cost associated with an individuals' hospital admissions per practice-quarter adjusted for price inflation (CPI).[7] Sourced from the NMDS.	-

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

[4] See https://nsfl.health.govt.nz/accountability/performance-and-monitoring/data-quarterly-reports-and- reporting/ambulatory-sensitive. Retrieved on July 9, 2018.
[5] See https://www.hqmnz.org.nz/library/Acute_readmissions_to_hospital. Retrieved on July 9, 2018. 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; McHugh & Ma, 2013). Considering 28-day readmissions does not affect our regression estimates.
[6] The measure takes positive values when the observed length of stay exceeds the diagnosis-related group-specific mean and negative for the reverse (Zhan & Miller, 2003; Mutter, Rosko, & Wong, 2008; Jiang & Pacheco, 2014).
[7] Health costs at the societal level encompass costs at the practice and hospital level – however, due to data availability our focus is only on the latter, costs to hospitals.

Table 2 presents descriptive information of all the variables in Table 1 over our sample timeframe. The registered Compass population consists of 235,485 individuals from 55 practices. This population is made up of 104,616 registered patients in HCH practices, and 130,869 in non-HCH practices. Once merged with the NMDS data, we find that 68,757 individuals from the Compass population had experienced a hospital event at least once during our study period (30,683 registered with an HCH practice, and 38,074 registered with a non-HCH practice). It is however important to note that each observation in Tables 2 and 3 (which presents descriptive information of the health events of interest and other covariates) represents a registered individual at each practice-quarter level. This means that each individual can appear multiple times in the analysis sample.

Table 2: Descriptive statistics of health events

	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) ✓	1.053%	0.998%	1.124% [1.086; 1.131]	0.000
Excess length of stay (duration) +	-0.007	-0.007	-0.006 [-0.006; -0.007]	0.271
Acute admission✓	1.608%	1.561%	1.671% [1.596; 2.042]	0.000
Frequency of acute admissions	0.019	0.019	0.020 [0.019; 0.025]	0.000
ED admission✓	1.448%	1.475%	1.413% [1.333; 1.812]	0.000
Frequency of ED admissions	0.016	0.016	0.015 [0.014; 0.020]	0.000
ASH event✓	0.558%	0.533%	0.590% [0.564; 0.722]	0.000
Frequency of ASH events	0.006	0.006	0.006 [0.006; 0.008]	0.000
Readmission✓	0.187%	0.180%	0.195% [0.185; 0.247]	0.006
Frequency of readmissions	0.002	0.002	0.003 [0.002; 0.002]	0.012
Average cost (CPI-adjusted)	96.936	90.121	105.913 [119.401; 160.530]	0.000
Doctor consultations/registrations*	0.619	0.609	0.641 [0.641; 0.651]	0.005
Non-doctor consultations/ registrations*	0.172	0.161	0.199 [0.188; 0.269]	0.008
Observations	2,977,682	1,692,647	1,285,035	

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.

+ Duration of excess length of stay can take both negative and positive values depending on the difference between observed length of stay and the diagnosis-related group-specific mean length of stay.

* The means for doctor and non-doctor consultations / registrations are based on a smaller population of 824 and 780 observations at the practice-quarter level.

Table 2 presents the mean estimates for each of our health events of interest. These are classified by HCH and non-HCH practices, and for the HCH practices, the descriptive information is further split into pre and post-HCH implementation (i.e. t=0 versus t=1). It is worth noting that while the incidence of health events of interest appear to increase marginally during the post-intervention period (third column), the actual effect of the HCH model can only be estimated when the change in these health events are evaluated in relation to a comparable group of non-HCH practices. In the empirical analysis that follows, we use difference-in-differences modelling, and a robustness check that incorporates propensity score matching. This method allows us to select a comparable group of non-HCH practices for the treatment group based on the registered population's characteristics before estimating our main regressions.

In Table 2, we also find that the health events of interest are significantly more prevalent in HCH-practices, compared to non-HCH practices. In particular, except for the duration of excess length of stay, the difference between the mean/ proportion of each health event is statistically significant at least at the 5 percent level. These differences are further substantiated in Table 3 where we look at the socio-demographic profiles (by gender, age, ethnicity and socio-economic deprivation[8]) of the registered population in the two types of practices.

The evidence on the significant differences in the health and demographic characteristics across practices that implemented the HCH model and the ones that did not, indicate that the implementation of HCH may not be randomly assigned. Therefore, our empirical analysis tests the consistency of our regression estimates by estimating multiple specifications, ranging from a baseline model to more saturated versions, that account for unobserved heterogeneities that may affect the true regression estimate. More specifically, exclusion of unobserved characteristics which are likely to be related to both HCH implementation and the health events analysed may result in biased estimates.

[8] All variables provided in Table 3 are used as covariates in the forthcoming regression analysis. The reference groups for the respective controls are male, 80 years and above, other ethnicity, and highest deprivation.

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	52.13	52.25	51.96	0.00
Male	47.87	47.75	48.04	0.00
Age				
Under 10 years	12.48	11.38	13.94	0.00
10-19 years	12.04	11.76	12.41	0.00
20-29 years	11.44	12.74	9.72	0.00
30-39 years	12.75	13.26	12.06	0.00
40-49 years	16.18	16.52	15.74	0.00
50-59 years	15.16	15.45	14.78	0.00
60-69 years	10.88	10.81	10.96	0.00
70-79 years	6.30	5.70	7.08	0.00
80 years and above	2.78	2.38	3.00	0.00
Ethnicity				
European	71.50	72.86	69.72	0.00
Māori	8.72	7.72	10.05	0.00
Pacific Peoples	5.42	5.83	4.89	0.00
Asian	10.51	10.36	10.72	0.00
MELAA	1.18	1.01	1.39	0.00
Others	2.23	1.84	2.74	
Socio-economic deprivation: Quintile				
1- Lowest deprivation	35.15	35.02	35.32	0.00
2	24.31	23.55	25.32	0.00
3	18.48	17.82	19.34	0.00
4	13.07	13.52	12.49	0.00
5- Highest deprivation	8.99	10.10	7.52	0.00
Observations	2,977,682	1,692,647	1,285,035	

Notes: MELAA = Middle Eastern, Latin American and African.

All variables are converted to binary indicators such that the estimates represent proportion of each demographic group specified on the left-hand side of the table. Each observation is at the individual-practice-quarter level.

4. Empirical Strategy

4.1 Difference-in-differences estimation

To analyse the effects of the HCH model on patient and practice-specific health events, we take advantage of the variation in timing of implementation of HCH across practices and employ difference-in-differences analysis. In particular, we estimate four empirical models ranging from a baseline model 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 represented by:

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

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 which equals 0 for all non-HCH practices and for the pre-intervention period of HCH practices. The time fixed effects λ_t account for time-specific factors that may affect all practices as well the health events of interest.

γ_p represents the practice-specific fixed effects incorporate time-invariant unobserved variables that are specific to each practice. v_{ipt} represents the error term in Model 1. α_1 estimates the association between HCH intervention and the health events evaluated in our study.

In Model 2, we add socio-demographic controls including age, sex, ethnicity and socio-economic deprivation index (measured in quintiles) that represents the economic conditions of regions / neighbourhoods that an individual resides in. The descriptive information of the individual level controls are provided in Table 3. Model 2 is:

$$Y_{ipt} = \beta_0 + \beta_1 HCH_{pt} + \beta_2' X_{ipt} + \gamma_p + \lambda_t + u_{ipt} \quad (2)$$

In addition to the variables described in equation (1), X_{ipt} is a vector of individual characteristics (sex, ethnicity, age, socio-economic condition). Including these variables is expected to increase the precision of the regression estimates obtained in equation 1. Further, it accounts for the differences in the observable characteristics between HCH and non-HCH practices in terms of the socio-demographic status of the registered population. Note that the reference groups used in our analysis are male, 80 years and above, other ethnicity, and highest socio-economic deprivation.

In Model 3, we add practice-specific linear time trends by interacting the time dummies with practices (Angrist & Pischke, 2013). Given that we are evaluating a non-random assignment of health care intervention (which is partially indicated in the significant difference in the sample means of socio-demographic characteristics of HCH and non-HCH population in Table 3), Model 3 is estimated to reduce biases in our regression coefficients. In particular, these biases may arise from exclusion of unmeasured variables that may affect both HCH implementation and individuals. Incorporating practice-specific linear time trends in addition to the controls used in Model 2 account for unobserved heterogeneities that evolve linearly over time. Model 3 is given by:

$$Y_{ipt} = \delta_0 + \delta_1 HCH_{pt} + \delta_2' X_{ipt} + \gamma_p + \lambda_t + \Omega_s t + e_{ipt} \quad (3)$$

$\Omega_s t$ in equation (3) is the practice-specific linear time trend and δ_1 estimates the relationship between HCH implementation and health outcomes.

In the final model (Model 4), we incorporate a parameterized event study in the regression to control for anticipatory and post-treatment effects of HCH implementation (Autor, 2003; Angrist & Pischke, 2013). Model 4 is:

$$Y_{ipt} = \rho_0 + \rho_1 HCH_{pt} + \rho_2' X_{ipt} + \theta_1 \delta_{st} + \theta_2 (\delta_{st} * HCH_{pt}) + \gamma_p + \lambda_t + \epsilon_{ipt} \quad (4)$$

In equation (4), we account for the possibility of the treatment endogeneity (discussed above) by controlling for a pre-treatment trend δ_{st} that is a measure of a quarter t relative to the time of HCH implementation. In this final model we also include an interaction between the pre-treatment trend and our key variable with respect to HCH implementation ($\delta_{st} * HCH_{pt}$). More specifically, while δ_{st} equals 0 for all non-HCH practices (for the entire study period) and for HCH practices at the time of implementation, the variable is negative for the pre-treatment period and positive for post-intervention quarters. For example, if a practice implements HCH in the third quarter of 2016, δ_{st} equates to -2 for the first quarter of 2016; -1 for the second quarter of 2016; 0 for the third quarter; 1 for the fourth quarter of 2016; 2 for the first quarter of 2017 and so on. Therefore, θ_1 estimates the pre- implementation trend in the health events of interest, while θ_2 identifies the difference in the health events before and after the implementation of HCH. If θ_1 is statistically significant, policy endogeneity may be present. While the anticipatory effects of the HCH assignment may vary across quarters depending on how close they are to the implementation time, controlling for δ_{st} and ($\delta_{st} * HCH_{pt}$) allows us to account for potential sources of bias that may affect causal interpretation of our main regression estimate ρ_1.

Across all four specifications, we estimate probit models for the binary health events (indicator of incidence of health events) and ordinary least squares regressions for the frequency of the health events. In all our regressions, the standard errors are corrected for clustering at the practice- level to address heteroscedasticity.

4.2 Robustness analysis

In addition to the above-mentioned specifications, we perform a supplemental analysis that combines our difference-in-differences model with a propensity score matching method that uses the empirical approach recommended by Khandker, Koolwal and Samad (2009). The matching method allows us to select a comparable group of non-HCH practices for the treatment group, based on the registered population's characteristics, before estimating our main regressions.

More specifically, by regressing the treatment indicator (using non-linear regression) on the pre-intervention proportions of socio-demographic characteristics (age, sex, ethnicity and quintile) associated with each practice, we generate propensity scores (Becker & Ichino, 2002). The propensity scores (generated from a logistic regression) represent the likelihood of a practice using the HCH model based on the socio-demographic characteristics of the population they serve.

The successful identification of the matched sample relies on satisfying a 'balancing property' that ensures that HCH is orthogonal (independent) to the socio-demographic covariates conditional on the propensity scores. Upon ensuring the balancing hypothesis, the practices are stratified into seven 'blocks' generated in a way 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 dropped from the sample (Khandker, Koolwal, & Samad, 2009) resulting in a final sample of 45 matched practices.

Using the matched practices, we subsequently re-estimate the four difference-in-differences models represented by equations (1) through to (4) as our additional robustness analyses.

5. Results

We report our difference-in-differences estimates with respect to the incidence of the health events of interest in Table 4. As discussed in the previous section, we estimate four models represented by equations (1) to (4). In the baseline regression models (Models 1 and 2), we do not find any regression coefficients across the health events that are statistically significant except for the indicator for ED admissions in Model 1 (column 3). In particular, for Model 1, we find that implementation of HCH results in a drop in the likelihood of an individual experiencing an ED admission by 0.1 percentage points per practice-quarter. This result is significant at the 5 percent level.

The negative relationship between HCH implementation and ED admissions holds across the more saturated models as well (Models 2 through to 4). In particular, when we additionally control for practice-specific linear time trends in Model 3, and for anticipatory effects of HCH implementation in Model 4, the marginal effects remain closely similar to our baseline regression estimates represented in Model 1. Interpreting the regression estimates in Table 4 as a proportion of the respective sample mean, the marginal effects for ED admissions in Model 3 translates to a 7.4 percent drop per individual-practice-quarter (marginal effect / sample mean = 0.00111 / 0.015). While in Model 4, the proportion rises slightly, representing a drop of 9 percent (0.00135 / 0.015) per individual-practice-quarter. The significant negative relationship between HCH and the incidence of ED admissions is consistent with the existing evidence in the current literature (Compass Health. 2017b; Ernst & Young, 2018).

Importantly in Model 4, referring to the marginal effects of the pre-treatment trend, we do not find any strong evidence of policy endogeneity. To put it more simply, the statistically insignificant regression coefficients of the pre-treatment trend for all the dependent variables (in Model 4 of Table 4) indicate that there may not be significant variation in the health events of interest during the periods leading up to the implementation of HCH.

Table 4: Difference-in-differences model with binary health events

	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

Notes: The marginal effects from probit regressions 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.

In Table 5, we re-estimate the four specifications for the intensity of the health events, as well as average hospital cost associated with the hospital admissions per individual-practice-quarter. For the most part we do not find any significant association between HCH implementation and the dependent variables (bar frequency of ED admissions).

In Models 3 and 4 we find statistically significant effects of HCH implementation on the frequency of ED admissions. In Model 3, HCH implementation results in a drop in the number of emergency events by 0.002 units, which is interpreted in terms of number of emergency events a person experienced in the study period. This effect is equivalent to12.5 percent relative to the sample mean. In the most saturated specification (Model 4), we find that HCH implementation results in a drop in the number of emergency admissions by 0.001 (6.3 percent relative to the sample mean) per individual-practice-quarter. The regression coefficients in both Models 3 and 4, with respect to the frequency of ED admissions, are statistically significant at the 5 percent level.

Table 5: Difference-in-differences model with intensity of health events

	Dependent variables (intensity of health events)					
	Duration of excess stay	Number of acute admissions	Number of ED admissions	Number of ASH events	Average actual cost	Number of readmissions
Sample mean	-0.007	0.019	0.016	0.006	96.936	0.002
Model 1: Time and practice-specific fixed effects						
HCH implementation	0.00139 (0.00203)	-0.00018 (0.00064)	-0.00104 (0.00069)	-0.00030 (0.00036)	2.657 (6.456)	-0.00012 (0.00028)
Model 2: Model 1 + demographic controls (age, sex, ethnicity, quintile)						
HCH implementation	0.00140 (0.00203)	-0.00014 (0.00061)	-0.00102 (0.00071)	-0.00031 (0.00036)	2.895 (6.213)	-0.00011 (0.00027)
Model 3: Model 2 + practice-specific linear time trends						
HCH implementation	0.00002 (0.00316)	-0.00068 (0.00073)	-0.00170** (0.00069)	-0.00039 (0.00034)	-0.799 (4.239)	-0.00018 (0.00049)
Model 4: Model 2 + event study						
HCH implementation	-0.00012 (0.00314)	-0.00005 (0.00069)	-0.00099** (0.00046)	-0.00014 (0.00032)	4.079 (4.923)	-0.00009 (0.00042)
Pre-treatment (δ_{pt})	0.00005 (0.00022)	0.00012 (0.00009)	-0.00005 (0.00012)	0.00005 (0.00004)	0.741 (0.852)	0.00003 (0.00002)
δ_{pt}X HCH implementation	0.00079 (0.00081)	-0.00045* (0.00025)	0.00016 (0.00025)	-0.00029** (0.00012)	-3.279* (1.645)	-0.00011 (0.00011)
Observations	2,977,682					

Notes: The OLS coefficients are 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

Next, to conduct the robustness analysis described in Section 4.2 we combined the differences-in-differences estimation with the propensity score matching method. As shown in Tables 6 and 7, we found similar results (to those illustrated in Tables 4 and 5) for both the binary indicators and the frequency of health events of interest. In particular, there continues to be evidence of HCH implementation resulting in a significant negative impact on ED admissions, as well as the number of ED admissions (in the saturated models 3 and 4 for the latter outcome of interest).

Table 6: 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 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	-0.00039*	-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

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.

Table 7: Difference-in-differences model with intensity of health events using practices selected from propensity score matching

	Dependent variables (intensity of health events)				
	Number of acute admissions	Number of ED admissions	Number of ASH events	Average actual cost	Number of readmissions
Sample mean	0.019	0.015	0.006	99.350	0.002
Model 1: Time and practice-specific fixed effects					
HCH implementation	-0.00037 (0.00065)	-0.00091 (0.00070)	-0.00035 (0.00036)	1.543 (6.563)	-0.00018 (0.00029)
Model 2: Model 1 + demographic controls (age, sex, ethnicity, quintile)					
HCH implementation	-0.00029 (0.00062)	-0.00088 (0.00072)	-0.00035 (0.00036)	1.942 (6.323)	-0.00016 (0.00028)
Model 3: Model 2 + practice-specific linear time trends					
HCH implementation	-0.00076 (0.00075)	-0.00177^{***} (0.00063)	-0.00040 (0.00035)	-0.133 (4.358)	-0.00024 (0.00050)
Model 4: Model 2 + event study					
HCH implementation	-0.00012 (0.00071)	-0.00098^{**} (0.00044)	-0.00013 (0.00033)	4.230 (5.015)	-0.00014 (0.00043)
Pre-treatment (δ_{pt})	0.00011 (0.00009)	-0.00003 (0.00013)	0.00005 (0.00004)	0.533 (0.868)	0.00003 (0.00002)
δ_{pt}X HCH implementation	-0.00045^{*} (0.00025)	0.00015 (0.00025)	-0.00031^{**} (0.00012)	-3.198^{*} (1.681)	-0.00010 (0.00011)
Observations	2,698,283				

Notes: The estimated coefficients and standard errors (in parentheses) from OLS 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.

Finally, we analysed the effects of HCH at the practice level by examining the impact on doctor and nurse consultation rates (defined by number of consultations / registered population). The results of this additional analysis are provided in Table 8 and signal no significant impact on these outcomes at the practice-quarter level.

Unfortunately we have no further practice level data to examine other types of outcomes. There are two types of variables that would have been useful for further analysis. First, variables that are available before and after implementation, such as wait times in the practice, number of age standardised patients enrolled per full time equivalent doctor (and nurse), staff turnover, and patient experience survey scores. A second set of variables that would also be useful for future research in this space are ones that are only available post HCH implementation. For example, data on use of the patient portal, the number of virtual consults (via telephone / video), the number of calls to the patient access centre, call abandonment rates, etc. It would be useful to follow trends in these indicators over time to build a contextual backdrop of changes at the practice level post HCH implementation.

Table 8: Estimation of the impact of HCH on consultations rate

	Dependent variables	
	Doctor consultations / registrations	Non-doctor consultations/ registrations
Sample mean	0.619	0.172
Model 1: Time and practice-specific fixed effects		
HCH implementation	-0.00604	0.00813
	(0.0171)	(0.0232)
Model 2: Model 1 + demographic controls		
HCH implementation	0.00580	0.00605
	(0.0131)	(0.0206)
Model 3: Model 2 + practice-specific linear time trends		
HCH implementation	0.0175	-0.0106
	(0.0163)	(0.0157)
Model 4: Model 2 + event study		
HCH implementation	0.0152	-0.0282
	(0.0123)	(0.0181)
Pre-treatment (δ_{pt})	-0.00178	0.00381
	(0.00140)	(0.00263)
δ_{pt}X HCH implementation	0.000356	0.00856
	(0.00498)	(0.00660)
Observations	824	780

Notes: The standard errors reported in parentheses are corrected for clustering at the practice-level. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels respectively.

6. Conclusions

This study explores early evidence on the impact of HCH implementation on important health-related events in the NZ context. The events considered in the analysis included the prevalence of ED admissions, acute admissions, ASH events, excess length of stay, and hospital cost. For many of these, both the binary indicator and intensity variable were investigated. One of the major advantages of this study is the use of administrative data which permits a population-based perspective. Despite the fact that our analysis is a case study limited to the Wellington region, the key findings contribute to international health literature in the related research space by evaluating the impact of a large-scale health care intervention intended to improve the quality of primary healthcare and reduce pressure on hospital services.

Given the recency of the implementation of HCH in Wellington, our analysis focusses on its short-term impact. Therefore, the statistically insignificant effects observed across most of the health events considered in the difference-in-differences analyses indicate that the health benefits of HCH may not be realized within a limited span of time after HCH implementation. This may be because we are assessing mostly hospital events in this analysis, which are downstream from the immediate impacts expected at the practice level. Unfortunately, we only had access to one general variable at the practice level – number of doctor (and nurse) consultations per registered population. Future analysis should definitely aim for a greater range of indicators at the practice level for empirical investigation.

Another potential reason for the lack of impact on the majority of hospital events is adjustment time costs that may be associated with both the healthcare service users (and providers) in adapting to the new features of HCH.

Our main finding is a small but statistically significant drop in the prevalence of ED admissions. This impact aligns with one of the primary objectives of the health care model. Importantly, this central finding is consistent across multiple empirical specifications employed to test the robustness of our regression findings. It is also consistent regardless of whether we focus on the binary indicator of ED admissions, or the frequency of ED admissions.

Finally, it is important to point out that future research should also focus on the long-term outcomes of HCH implementation. As mentioned earlier, for the 11 practices under investigation, the maximum time period post HCH implementation was five quarters, hence providing evidence of the short run impact. Further data beyond our study period would be required for an analysis of long term outcomes.

7. References

Amarasingham, R., Moore, B. J., Tabak, Y. P., Drazner, M. H., Clark, C. A., Zhang, S., ... Halm, E. A. (2010). An automated model to identify heart failure patients at risk for 30-day readmission or death using electronic medical record data. *Medical Care, 48*(11), 981-988. https://doi.org/10.1097/MLR.0b013e3181ef60d9

Angrist, J. D., & Pischke, J. S. (2013). *Mostly harmless econometrics: An empiricists companion*. United States: Cram101 Publishing.

Autor, D. H. (2003). Outsourcing at will: The contribution of unjust dismissal doctrine to the growth of employment outsourcing. *Journal of Labor Economics, 21*(1), 1-42. https://doi.org/10.1086/344122

Becker, S. O., & Ichino, A. (2002). Estimation of average treatment effects based on propensity scores. *The Stata Journal,* 2(4), 358-377. Retrieved from https://www.stata-journal.com/article.html?article=st0026

Capital & Coast District Health Board. (2018). *Community Public Health Advisory Committee*. Retrieved from https://www.ccdhb.org.nz/about-us/advisory-committees/cphac-final-public-agenda-12-feb-2018.pdf

Compass Health. (2017a). *Compass Health annual report 2017*. Retrieved from http://annualreport.compasshealth.org.nz/2017/docs/Compass_Health_2017_Annual_Report.pdf

Compass Health. (2017b). *Health Care Home first year: Achievements and reflections.* Retrieved from http://www.compasshealth.org.nz/Portals/0/HCH/HCH-year-1-reflections.pdf

Compass Health. (2018). *Health Care Home practices*. Retrieved June 10, 2018, from http://www.compasshealth.org.nz/PracticesandFees/HealthCareHomePractices.aspx

Downs, A. (2017). *From theory to practice: The promise of primary care in New Zealand*. Retrieved from http://www.fulbright.org.nz/wp-content/uploads/2017/09/DOWNS-From-Theory-to-Practice-The-Promise-of-Primary-Care-in-New-Zealand-.pdf

Ernst & Young. (2017). *Evaluation of the New Zealand Health Care Home, 2010-2016*. Retrieved from http://www.healthcarehome.co.nz/wp-content/uploads/2017/03/EY-Health-Care-Home-Evaluation-2017.pdf

Ernst & Young. (2018). *Health Care Home evaluation: Updated analysis April-September 2017*. Retrieved from http://www.healthcarehome.co.nz/wp-content/uploads/2018/05/EY-HCH-Evaluation-April-18.pdf

Grant, R., & Greene, D. (2012). The health care home model: primary health care meeting public health goals. American Journal of Public Health, 102(6), 1096-1103.

Gilfillan, R.J., Tomcavage, J., Rosenthal, M.B., Davis, D.E., Graham, J., Roy, J.A., Pierdon, S.B., Bloom, J.F., Graf, T.R., Goldman, R. and Weikel, K.M., (2010). Value and the medical home: effects of transformed primary care. The American journal of managed care, 16(8), 607-614.

Health Care Home Collaborative. (2017). *Health Care Home model of care requirements.* Retrieved from http://www.healthcarehome.co.nz/wp-content/uploads/2017/07/Health-Care-Home-Model-of-Care-Requirements.pdf

Hefford, M. (2018). From good to great: the potential for the Health Care Home model to improve primary health care quality in New Zealand. *Journal of Primary Health Care, 9*(3), 230-233. https://doi.org/10.1071/HC17045

Jackson, G., & Tobias, M. (2001). Potentially avoidable hospitalisations in New Zealand, 1989–98. *Australian and New Zealand Journal of Public Health, 25*(3), 212-221. https://doi.org/10.1111/j.1467-842X.2001.tb00565.x

Jiang, N., & Pacheco, G. (2014). Demand in New Zealand hospitals: expect the unexpected?. *Applied Economics, 46*(36), 4475-4489. https://doi.org/10.1080/00036846.2014.964830

Khandker, S., B. Koolwal, G., & Samad, H. (2009). *Handbook on impact evaluation: Quantitative methods and practices.* Washington, D.C: The World Bank.

Maeng, D.D., Graham, J., Graf, T.R., Liberman, J.N., Dermes, N.B., Tomcavage, J., Davis, D.E., Bloom, F.J. and Steele, J.G., (2012). Reducing long-term cost by transforming primary care: evidence from Geisinger's medical home model. The American journal of managed care, 18(3), 149-155.

McCarthy, D., Mueller, K. & I. Tillman. (2009). Group health cooperative: Reinventing primary care by connecting patients with a medical home. Retrieved from https://www.commonwealthfund.org/sites/default/files/documents/___media_files_publications_case_study_2009_jul_1283_mccarthy_group_health_case_study_72_rev.pdf

McHugh, M. D., & Ma, C. (2013). Hospital nursing and 30-day readmissions among Medicare patients with heart failure, acute myocardial infarction, and pneumonia. *Medical Care, 51*(1), 52-59. https://doi.org/10.1097/MLR.0b013e3182763284

Middleton, L., Dunn, P., O'Loughlin, C. & J. Cumming. (2018). Taking stock: Primary care innovation. Retrieved from https://www.productivity.govt.nz/sites/default/files/Taking%20Stock%20Primary%20Care%20Innovation_Victoria%20University%20Wellington.pdf

Mutter, R. L., Rosko, M. D., & Wong, H. S. (2008). Measuring hospital inefficiency: The effects of controlling for quality and patient burden of illness. *Health Services Research, 43*(6), 1992-2013. https://doi.org/10.1111/j.1475-6773.2008.00892.x

Pinnacle Midlands Health Network. (n.d.). *Health Care Home overview*. Retrieved June 10, 2018, from http://www.healthcarehome.co.nz/overview/

Reid, R.J., Coleman, K., Johnson, E.A., Fishman, P.A., Hsu, C., Soman, M.P., Trescott, C.E., Erikson, M. and Larson, E.B. (2010). The group health medical home at year two: cost savings, higher patient satisfaction, and less burnout for providers. Health affairs, 29(5), 835-843.

Zhan, C., & Miller, M. R. (2003). Excess length of stay, charges, and mortality attributable to medical injuries during hospitalization. *JAMA, 290*(14), 1868-1874. https://doi.org/10.1001/JAMA.290.14.1868

Appendix A: 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	1773	1781	1803	1822	1829	1835	1864	1874	1888	1893	1924	1947	1968	1995	2040	2079
2016 3rd quarter	2	8302	8488	8641	8841	9005	9183	9360	9609	9805	9975	10244	**10471**	**10742**	**10987**	**11257**	**11645**
	3	1403	1428	1472	1507	1537	1557	1594	1622	1696	1683	1750	1792	1864	1925	2004	2104
	4	373	387	395	412	420	429	442	457	462	471	476	490	514	531	549	587
	5	2567	2607	2646	2700	2732	2769	2833	2847	2901	2946	3001	3077	3159	3240	3316	3414
2017 4th quarter	6	3201	3246	3305	3370	3442	3541	3650	3727	3863	3947	4073	4212	4355	4503	4659	4850
2016 4th quarter	7	1759	1808	1826	1843	1867	1911	1952	1985	2023	2044	2108	2136	**2205**	**2257**	**2287**	**2357**
	8	6584	6726	6872	7066	7287	7436	7632	7797	7976	8136	8430	8638	8860	9090	9333	9683
	9	693	713	724	732	757	767	784	799	811	830	849	860	877	901	923	954
	10	3523	3613	3723	3845	3981	4132	4298	4513	4687	4824	5053	5224	5430	5614	5790	5964
	11															444	449
2017 3rd quarter	12	5737	5844	5974	6121	6237	6390	6553	6703	6953	7153	7406	7633	7815	8112	8350	**8673**
	13	855	880	892	921	952	972	1001	1043	1070	1115	1152	1177	1218	1279	1353	1421
	14	641	651	665	681	725	756	799	829	847	881	910	939	971	996	1025	1056
2018 2nd quarter	15	1892	1922	1975	2032	2105	2179	2296	2408	2556	2661	2847	2977	3154	3322	3485	3666
	16	2056	2086	2116	2145	2161	2190	2237	2281	2308	2330	2386	2411	2440	2485	2535	2609
	17	3796	3822	3887	3981	4073	4138	4191	4211	4273	4340	4367	4384	4441	4522	4561	4656
	18	2489	2532	2558	2623	2654	2679	2723	2754	2789	2831	2857	2913	2962	3020	3107	3185
2017 4th quarter	19	7005	7114	7236	7355	7481	7599	7705	8068	8196	8338	8486	8612	8779	9009	9198	9344
	20	149	156	254	281	302	367	557	597	632	764	979	1018	1053	1186	1458	1521
2018 1st quarter	21	6326	6381	6447	6568	6644	6714	6807	6879	6976	7086	7188	7260	7347	7458	7590	7720
2017 4th quarter	22															5360	5509
	23	373	381	382	387	401	410	418	433	437	438	441	453	468	485	497	501
	24	1616	1645	1649	1665	1682	1705	1724	1734	1743	1767	1794	1813	1832	1862	1892	1939
	25	2603	2654	2699	2749	2781	2862	2910	2961	3038	3124	3202	3299	3398	3486	3582	3712
	26	1850	1883	1886	1907	1919	1956	1972	1995	2015	2028	2060	2079	2093	2111	2144	2180
	27	1179	1213	1219	1256	1277	1343	1393	1438	1502	1546	1583	1627	1682	1762	1856	1959
	28	4683	4729	4801	4891	5004	5148	5270	5427	5589	5691	5940	6119	6379	6628	6814	7056
	29	3522	3569	3636	3691	3723	3767	3813	3890	3929	3977	3993	4087	4164	4285	4348	4429
	30	5031	5116	5190	5283	5378	5468	5567	5662	5750	5849	6005	6116	6230	6398	6531	6698

Appendix A (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	2033	2087	2134	2165	2172	2230	2323	2406	2488	2570	2667	2758	2866	2967	3073	3207
	32	3539	3600	3631	3657	3688	3744	3813	3862	4006	4093	4211	4323	4421	4608	4723	4902
2017 3rd quarter	33	8146	8248	8353	8463	8639	8756	8871	8938	9048	9167	9336	9454	9596	9813	10002	**10207**
2016 4th quarter	34															5869	**6023**
2018 1st quarter	35	1598	1616	1634	1649	1666	1684	1701	1712	1733	1756	1782	1817	1860	1903	1932	1991
	36	1248	1261	1281	1298	1305	1348	1386	1420	1442	1466	1490	1503	1513	1544	1582	1607
2018 3rd quarter	37	4600	4655	4724	4798	4863	4924	5093	5157	5220	5310	5404	5507	5615	5734	5850	5988
	38	1609	1631	1672	1704	1721	1741	1763	1770	1774	1780	1807	1830	1855	1864	1886	1913
	39	6626	6731	6817	6903	7011	7098	7170	7257	7332	7463	7585	7699	7828	7969	8122	8293
	40	4232	4366	4409	4490	4552	4622	4712	4776	4869	4962	5043	5103	5203	5321	5462	5586
	41	1874	1883	1919	1965	1991	2036	2140	2172	2239	2245	2307	2354	2394	2468	2506	2574
2016 3rd quarter	42	2198	2240	2301	2327	2362	2372	2401	2426	2474	2508	2548	**2597**	**2631**	**2680**	**2745**	**2822**
	43	2251	2276	2298	2322	2364	2413	2481	2542	2592	2641	2703	2750	2816	2868	2933	3012
	44	3074	3113	3135	3169	3199	3229	3253	3273	3319	3345	3418	3491	3543	3600	3650	3731
	45	5584	5641	5734	5853	5948	6060	6147	6259	6373	6481	6641	6751	6873	7052	7231	7440
	46	4417	4451	4517	4598	4718	4770	4866	4985	5072	5180	5305	5421	5522	5653	5811	5943
2017 4th quarter	47	3137	3204	3252	3336	3417	3475	3513	3542	3598	3634	3768	3826	3890	3950	4028	4148
	48													127	285	508	742
	49	1271	1276	1687	1886	2003	1900	2535	2944	3035	2767	3932	4382	4446	4160	5959	6679
	50	269	278	276	286	283	295	313	331	344	351	360	373	387	411	431	452
	51	1576	1623	1668	1728	1750	1774	1816	1851	1876	1912	1958	1992	2032	2090	2152	2289
2018 1st quarter	52	4143	4201	4258	4292	4328	4371	4443	4469	4549	4623	4712	4771	4872	4965	5054	5173
2018 2nd quarter	53	3859	3967	4055	4131	4172	4255	4363	4435	4508	4596	4659	4734	4842	4955	5066	5231
2016 3rd quarter	54	6676	6751	6805	6860	6939	7063	7176	7281	7413	7501	7618	**7720**	**7870**	**8063**	**8257**	**8452**
	55	1990	2017	2049	2090	2131	2172	2212	2256	2303	2351	2385	2414	2448	2510	2585	2646

Notes: The practice identifiers marked in red implemented the health care homes model. Red also indicates the quarter of implementation, while **green and bold** indicates the quarters post-implementation.