Three Essays on Technology and Healthcare

By

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Abstract

Advances in medical technology have changed the standards of models of care, while also constituting a driving force in raising costs. This thesis addresses the various impacts of technology on healthcare through three chapters.

The first chapter investigates to what extent medical technology drives healthcare expenditure for a panel of Canadian provinces and another of OECD countries. A careful examination of existing technology proxies is conducted, and three new proxies are added to the literature. A novel dynamic common correlated effect approach from the emerging field of panel time series is employed to explore the relationship between healthcare expenditure and technology. As expected, the variables are tied-together by a long-run relationship, but the speed of adjustment varies depending on the technology proxy used and the level of aggregation.

The second and third chapters study the effect of two forms of health information technology on a variety of healthcare and health outcomes. Specifically, two programs are investigated: telemedicine and electronic medical records (EMR). Both programs take place in the Canadian province of Manitoba. The linkable administrative data housed at the Manitoba Centre for Health Policy was used to create cohorts of users and non-users for each of the programs.

The second chapter uses a propensity-weighted regression model to measure the impact of telemedicine on four indicators of healthcare use. Results point to increased use of healthcare services for telemedicine users. But for those patients who showed higher intensity of use, telemedicine seems to be a substitute for regular care, and not an addition to it.

Finally, the third chapter explores the association, at a primary care level, between use of electronic medical records and quality of care measures. A set of indicators covering preventive care, chronic disease management, and healthcare utilization are investigated through a difference-in-differences approach with patient and time fixed effects, and an estimation strategy that uses the variation in timing of adoption. Results show that patients with diabetes in primary care practices using EMR's show improved management indicators, while no evidence of changes in preventive care or hospitalizations for a set of ambulatory care sensitive conditions is found.

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List of Abbreviations

ACSC: Ambulatory Care Sensitive Conditions

ADF: Augmented Dickey Fuller Unit Root Test

CAD: Canadian Dollars

CD: Pesaran Test for Cross-Section Dependence

CIHI: Canadian Institutes for Health Information

COCI: Continuity of Care Index

COPD: Chronic Obstructive Pulmonary Disease

CTR: Clinical Trial Recruitments

DCCE-MG: Dynamic Common Correlated Effects Mean Group Estimator

ECM: Error Correction Model

EMR: Electronic Medical Records

EHR: Electronic Health Records

GDP: Per Capita Income

HCE: Per Capita Healthcare Expenditure

hdPS: High-Dimensional Propensity Scores

HIPC: Health Information Privacy Committee

HIT: Health Information Technology

HREB: University of Manitoba Health Research Ethics Board

ICD-10-CA: International Classification of Diseases, 10^{th} Revision, Canada

ICD-9-CM: International Classification of Diseases, 9^{th} Revision, Clinical Modification

IPTW: Inverse Probability of Treatment Weights

KPSS: Kwiatkowski, Phillips, Schmidt, and Shin Test

MaPCReN: Manitoba Primary Care Research Network

MBT: Manitoba Telehealth Program

MCHP: Manitoba Center for Health Policy

NAI: Newly-Marketed Drugs with New Active Ingredients

NDA: New Drug Approvals

NMD: Newly-Marketed Drugs

NME: New Molecular Entities

OECD: Organization for Economic Co-operation and Development

PCP: Primary Care Physicians

PMA: Medical Device Pre-Market Approvals

PMN: Medical Device Pre-Market Notifications

POP65: Proportion of the Population over 65 Years of Age

PUB: Public Share of the Expenditure

R&D: Research and Development

Repository: Population Health Research Data Repository

RHA: Regional Health Authority

RMSE: Root Mean Square Error

TECH: Medical Technology Proxy

USD PPP: U.S Dollar Purchasing Power Parity

Authorship Declaration

This thesis contains work that has been submitted (or it is in the process of being submitted) to peer-reviewed journals. The candidate (Elisabet Rodriguez Llorian) conceptualized and executed the work in collaboration with her thesis supervisors (Dr. Janelle Mann and Dr. Gregory Mason), and advisory committee. All authors on the manuscripts provided intellectual input on the study design, participated in interpretation of the results and assisted with preparation of manuscripts drafts. Elisabet Rodriguez Llorian takes full responsibility for the accuracy of the thesis and was responsible for statistical analysis and interpretation. All authors approved the final manuscripts.

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Introduction

Technology is generally believed to be a major factor contributing to healthcare spending increases. As defined by the World Health Organization, medical technology comprises every "application of organized knowledge and skills in the form of medicines, medical devices, vaccines, procedures and systems developed to solve a health problem and improve quality of life" (WHO, 2018). But the direction and extent of the impact of medical technology on healthcare expenditure is controversial.

With healthcare expenditure accounting for a significant portion of GDP in advanced economies, new technology and innovation in healthcare have been attracting increasing attention. Some researchers have argued that the health benefits derived from the rapid introduction and diffusion of new medical innovations are minimal despite their substantial contribution to the growth in expenditure. Accordingly, new goods and/or expansion of healthcare services resulting from new medical technologies may be regarded as a good thing only to the extent that they improve health outcomes (better quality or longer life). However, over the last decades, medical technology has greatly influenced the way healthcare is delivered, and the potential effect of technology on different healthcare outcomes is mixed.

While studying technology on one side and healthcare on the other this thesis addresses two main areas of research. First, the impact of technology on rising healthcare costs, and second, to what extent has medical technology change standards and quality of care. The existent literature is extensive, but as new technologies are developed and data becomes available questions emerge around how and why medical technology could contribute to cost-effective healthcare systems.

Results from this thesis will enable academic and policy makers to gain insights into how medical technology drives healthcare expenditure as well as how new technologies, specifically health information technology, contributes to improved healthcare attention and outcomes. The results from the thesis will point policy makers to the relevance of carefully considering implementation and development of these type of technologies, so as to facilitate informed choices. Understanding the factors involved, and the dynamics on how and why technology can serve to enhance diagnostic and treatment options, as well as quality of care (and ultimately quality of life), is crucial in exposing the results and future potential of new technology initiatives in the health field.

Research Questions

This thesis fills a gap in knowledge surrounding medical technology and its effects in healthcare. The richness of the administrative data in the Canadian province of Manitoba provided a unique opportunity to empirically examine the impact of different forms of medical technology on various health and healthcare outcomes. The following research questions are examined:

Question 1 (Chapter 1): To what extent is medical technology driving healthcare expenditure?

1.1 Does the choice in proxy for medical technology influence results?

1.2 Do existing proxies for medical technology successfully capture all conceptual dimensions and have desirable time series properties?

Question 2 (Chapter 2): What is the impact of telemedicine on healthcare utilization?

2.1 Does the impact differ for chronic conditions?

2.2 What are the patterns of use in terms of patients' characteristics, region, and type of providers?

Question 3 (Chapter 3): Is there a significant difference between health outcomes of patients before and after their primary care providers implemented electronic medical records (EMRs)?

3.1 Is the effect consistent across indicators of preventive care, chronic disease management and healthcare utilization?

3.2 Are there observable differences between physicians using EMRs and those not using EMRs, as well as between groups of users with different adoption timing?

Question 4 (Chapters 2 and 3): What are some of the limitations surrounding data collection in Manitoba that would support better measurement of the impact of telemedicine and EMRs?

While questions from chapter 1 investigate the impact of medical technology on health spending at an aggregate level, questions from the second and third chapters focus on the effect of specific technologies (namely telemedicine and EMRs) on health and healthcare outcomes. Results will shed light on whether the costly proliferation of technological innovations in healthcare have also resulted in improved quality of care (chapter 3); as well as an enhancement in delivery options and accessibility with subsequent changes in patterns of use - from in person visits to e-consults (chapter 2).

HIT and e-health

A substantial part of this thesis studies two specific types of medical technology in the healthcare sector, both related to information technology. Health information technology (HIT) is a subset of information technology (or the use of computers to store, transmit and manage data) that supports health information management across computerized systems and secure exchange of health information between healthcare users. HIT has been a feature of health care for over half a century and, according to Glaser (2016), IT in general (and by implication HIT), has experienced four waves and is well into the fifth:

1. Mainframe that allowed organizations to automate clerical and other routine tasks
2. Minicomputers created support for expanded clinical tasks and imaging
3. Networked PCs support shared storage and printing
4. Internet supports new ways for health practitioners and patients to interact
5. Nearly ubiquitous computing (Glaser's term) features large datasets, real time decision-making to coordinate complex treatment, and testing complex causal relationships

Various forms of HIT include health record systems (mainly EMRs); personal tools including smart devices and apps; and communities to share and discuss information (Open MRS, 2017); EMRs being the one form attracting most attention. Other healthcare innovations such as telemedicine (which allows the delivery of healthcare and related services over a distance) heavily relies on HIT. Telemedicine and EMRs can both be grouped under the term "e-health", closely related to HIT, only with more emphasis on the "health services and information delivered and enhanced through Internet and related technologies" (Eysenbach, 2001), rather than on the technology per se. Three main areas of e-health as described by Black et al. (2011)

are: storing, managing, and transmission of data; facilitating care from a distance; and clinical decision support.

Telemedicine and EMRs have been generally available in Canada since 2000 and straddle the fourth and fifth waves outlined above. In principle, proponents claim these technologies facilitate health care in three ways. First, they reduce costs to provider and patient; second, they expand the reach of treatment, notably for patients residing in remote areas; and third, they support improved treatment that result in better outcomes. But despite the many claimed benefits of HIT, clear demonstrations of the advantages remain elusive (Agha, 2014; Black et al., 2011; Lau et al., 2010).

One of the main challenges associated with the success of these forms of HIT is their usability and possibility to facilitate exchange of data. Concerns have been raised regarding the lack of standards in e-health architecture, interoperability, standards of reimbursement and the need of sound legal frameworks for protection of patient data (Hochman et al., 2019; WHO, 2012). Some of the recent literature has proposed cloud computing as a way to improve collaborative information issues in the medical fields through standardized cloud-based applications, and remote access capabilities (Nigam & Bhatia, 2016). Ratwani et al. (2019) laid out five main priorities for usability improvements in HIT including: the creation of a database of usability and safety issues, existence of basic design standards, need to explicitly address unintended harms, simplified mandated documentation requirements, and the creation of standard usability and safety measures.

There is also the belief that doctors are “burned” by the HIT industry, and that these new technologies have moved time and resources away from patient care into a profiting HIT sector

(Green, 2016); along with the general understanding that the implementation of these technologies are not a guarantee of achieved potential. Behind this, probably lies the importance of physician patient interaction. HIT applications such as EMRs and telemedicine might have, for some cases, not essentially changed the ways things are done, but merely making clinical processes burdensome (Lagasse, 2017; Sinsky et al., 2016). While it might be hard to imagine a world without online shopping or banking, HIT has not revolutionized the health sector to the extent initially envisioned by some of its supporters, and the importance of the "human" factor might be one reason.

Thesis Structure

This thesis addresses policy-relevant questions around the central topic of medical technology and its impact on healthcare with focus on the previously outlined research questions. These are developed in three separate, yet interrelated chapters.

The first chapter studies the effect of medical technology on healthcare expenditure between 1981 and 2016 for two panels that differ in level of aggregation (OECD countries and Canadian provinces), and introduces three new proxies for medical technology. The first proxy is a global proxy representing 204 countries, and the other two are country-level proxies from Canada. Results from a panel error correction model (ECM) estimated using the dynamic common correlated effect approach by Chudik & Pesaran (2015) reveal that medical technology and healthcare expenditure follow a long-run relationship. However, the speed at which the system returns to its long-run relationship depends on the choice of technology proxy and level of aggregation.

The provision of healthcare services through telemedicine is a potential alternative to in-person interactions between patients and physicians. But evidence is limited regarding patients' responses to this model of care. The second chapter empirically assesses whether telemedicine changes healthcare utilization. Administrative data from the Manitoba Centre for Health Policy is linked to records from the Manitoba Telehealth Program to conduct a population-level study. Using a novel dataset, the estimation strategy employs a propensity-weighted regression model, after conducting a high-dimensional propensity score method. Results indicate that, compared to non-users, telemedicine patients have higher number of face-to-face visits (with primary care physicians and specialists), as well as more hospitalizations. But for those patients who show a higher intensity of telemedicine use, telemedicine seems to be substituting for regular care, rather than adding to it.

Lastly, a third chapter explores the association, at a primary care level, between use of EMRs and quality of care measures. A set of indicators covering preventive care, chronic disease management, and healthcare utilization are studied for a panel of patients with continuous enrollment between 2009 and 2017. A difference-in-differences approach with patient and time fixed effects was estimated using population-based data for the Canadian province of Manitoba. The variation in timing of adoption was used for the estimation strategy. Patients with diabetes in primary care practices using EMR's show improved management indicators, while there is no evidence of changes in preventive care or hospitalizations for a set of ambulatory care sensitive conditions.

Research across all three chapters contributes to the understanding of two sides of innovation in healthcare: costs and benefits in terms of improved health outcomes and quality; it

also adds to current knowledge on the state of health information technology in Canada, and to issues surrounding their implementation and use. This is particularly relevant to academics in fields of health economics, population health and public policy, as well as to professionals in healthcare policy, planning and management in order to make informed decisions on cost-effective innovations that could increase overall quality and specialized support in healthcare services.

Ethical Considerations and Approvals

Chapter 1 does not use data collected from human subjects and therefore no ethics approval is required.

Chapters 2 and 3 use individual level de-identified administrative data, which reduces potential ethical issues as no direct contact with human subjects was made. In Manitoba, the administrative files from various government departments are de-identified by Manitoba Health, Seniors and Active Living, and these de-identified files are housed and linked at the Manitoba Centre for Health Policy. Data used for chapters 2 and 3 are from the Manitoba Population Research Data Repository housed at the Manitoba Centre for Health Policy, University of Manitoba and were derived from data provided by Manitoba Health, Seniors and Active Living, Winnipeg Regional Health Authority, Cancer Care Manitoba, and Manitoba Primary Care Research Network. Approvals from the different data providers were obtained, as well as from the Health Information Privacy Committee under project #2017/2018-48 (chapter 2) and project #2019/2020-07 (chapter 3); and the University of Manitoba Health Research Ethics Board (HREB) under project #HS21298 (H2017:378) (chapter 2) and project #HS22719 (H2019:131) (chapter 3). The required annual renewals of the HREB approval were completed. All data

providers have been notified of presentations and/or manuscripts submitted for publication. See Appendix D and E for all approvals.

The results and conclusions are those of the author and no official endorsement by the Manitoba Centre for Health Policy, Manitoba Health, Seniors and Active Living or other data providers is intended or should be inferred.

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Chapter 1. The Technology-Healthcare Expenditure Nexus: An investigation of OECD Member Countries and Canadian Provinces

Introduction

The extent to which medical technology drives healthcare expenditure has been the subject of much research in health economics since Newhouse's conjecture (Newhouse, 1992). A recent paper attributed 35% of the growth in healthcare expenditures to medical technology for OECD countries (Willemé and Dumont, 2015). But the way technology impacts healthcare expenditure depends on a variety of factors. These include whether a given technology substitutes for an exising service, expands the number of treatable conditions, or impacts the delivery of care (for example by improving capacity to treat more patients) (Sorenson et al., 2013). Likewise, while spending may increase rapidly at first when technology treats those who went without, it may slow over time as it substitutes for existing treatments that are more expensive (Cutler & Huckman, 2003).

The complexity of the technology-expenditure nexus is accentuated by the lack of a clear-cut definition for medical technology. Existing definitions, such as that by the World Health Organization (WHO, 2018), commonly include new procedures, treatments, drugs, medical equipment, as well as organizational systems. Due to the absence of a perfect measure that includes all categories, studies have (imperfectly) measured medical technology either as a residual (considering medical technology as the part of expenditure growth not explained by observable drivers), or using specific proxies. The latter varies from input measures (such as spending on research and development, number of drugs, and devices) to output measures

(including life expectancy and mortality). These measures are explained in the next section. The choice of proxy for medical technology, level of aggregation, empirical methods, and additional explanatory variables vary greatly across existing studies (please refer to Appendix A.1 for details), and contribute to the differing results for the role played by medical technology.

This paper adds to the existing body of literature in two ways. First, it provides a better understanding of how to quantify medical technology and introduces three new proxies based on the number of approved drugs and clinical trials. The newly introduced proxies offer conceptual depth. Second, it investigates the technology-healthcare expenditure nexus by employing a panel cointegration and error correction model (ECM) for data at two levels of aggregation: country level (OECD countries) and province level (Canadian provinces) for the years 1981 - 2016.

From a methods perspective, this study complements and builds on previous research that addresses the relationship between medical technology and healthcare expenditure using a panel time series approach (Roberts, 1999; de Mello Sampayo and de Sousa-Vale, 2014). Specifically, we investigate panel cointegration by estimating an error correction model (ECM) using the dynamic common correlated mean group estimator (DCCE-MG) by Chudik and Pesaran (2015). Our model overcomes problems of previous research by dealing with cross-section dependence, parameter heterogeneity, endogeneity problems, and stationarity of variables. It also allows us to obtain long run estimates for drivers of healthcare expenditure while testing for cointegration by investigating the significance of the error correction term.

Results from the panel ECM indicate that the system, which includes medical technology, follows a long-run relationship for both the panel of OECD member countries and Canadian provinces. However, the speed at which the system returns to its long-run relationship depends,

among other factors, on the measure of technology (proxy) and level of data aggregation. Estimations also show great heterogeneity in the technology effect on healthcare expenditure across countries and provinces, which points to a need to carefully consider policy recommendations on measures intended to control healthcare expenditures.

The paper continues by expanding on the literature considering medical technology as a key driver of healthcare expenditure, highlighting proxies for medical technology. The third section presents a review of other drivers of healthcare expenditure. The fourth section describes the data, and the fifth section explains the methodology. Results and robustness checks are presented in section six. The paper concludes with policy implications for decision-makers and guidance for researchers regarding the choice of technology proxy, level of aggregation, and methodology.

Technology and Healthcare Expenditure: Background Literature

A key element of the analysis when studying the relationship between medical technology and healthcare expenditure is the issue of how to measure medical technology. As defined by the World Health Organization, medical technology comprises every "application of organized knowledge and skills in the form of medicines, medical devices, vaccines, procedures and systems developed to solve a health problem and improve quality of life" (WHO, 2018). The challenge is finding a measure or statistical proxy that captures all dimensions of medical technology. Studies of drivers of healthcare expenditures have not agreed on the proxy or the effect of medical technology. Even when there is a consensus in the direction of the impact, the magnitude varies.

One way to address the absence of a precise measure for medical technology is to use the residual approach initially adopted by Newhouse (1992), and more recently by Chernew and Newhouse (2012), Rossen and Faroque (2016) and You and Okunade (2017). Following this method, the effect of observable drivers of healthcare expenditure (such as income) is subtracted from total growth in spending, attributing the residual effect to medical technology. However, this residual also accounts for other omitted variables, and might be overestimating the effect of technology. Results obtained from this approach should then be considered as the upper bound of the technology effect on healthcare expenditure (You and Okunade, 2017). Finding the impact of medical technology to be positive is a common result for studies adopting the residual approach.

Another way to address the absence of a precise measure is to use time to proxy medical technology, be it through a linear time trend (Bilgel and Trand, 2013) or time-specific intercepts (Di Matteo, 2005). Effects on healthcare expenditure vary from 3% to 65% respectively. A trend variable, however, neglects an explicit treatment of innovations and will account for any non-observed trended effects. It can also drastically affect the estimates of other determinants, and it is likely that its coefficients will not be robust due to collinearity with other trended variables (Robert, 1999). Furthermore, innovation in medical technology has not always been found to follow a monotonic increasing trend. For example, using a weighted sum of time dummies for a sample of Dutch hospitals Blank and Vogellar (2004) found medical technology to follow an erratic trend; with technology sometimes affecting expenditure in beneficial ways (Blank and Hulst, 2009).

Other proxies used to account for the effect of medical technology on expenditures include life expectancy (Dreger and Reimers, 2005) and infant mortality (Dreger and Reimers,

2005; de Mello-Sampayo and de Sousa-Vale, 2014; You and Okunade, 2017). Medical technology is expected to have a positive contribution to the health status of the population which is measured frequently by life expectancy and mortality indicators. Hence, the authors selected proxies based on the variable's relation to medical progress and found the estimated effects on healthcare expenditure to be around 30%. Using life expectancy and infant mortality shares most previously discussed disadvantages, including not modelling innovations explicitly and imposing an increasing trend.

Another widely used proxy for medical technology is R&D expenditures (Murthy and Okunade, 2016; Murthy and Ketency, 2017; You and Okunade, 2017). Medical technology is a significant determinant of healthcare expenditure across studies using R&D expenditures, with effects ranging from 18% to 40%. In contrast, Hauck and Zhang (2016) include 43 drivers of healthcare expenditure and R&D was not one of 16 significant drivers. The use of R&D as a proxy for medical technology has been criticized for only including the input of innovation, usually does not result in any meaningful advancement (Willemé and Dumont, 2015). Additionally, limitations of the industry classification that is used to measure for R&D have been raised by Pammolli et al. (2005). For example, for European countries, low technology submarkets of the health sector are not considered, which excludes for example high tech biochemicals devices such as in vitro diagnostics (Pammolli et al., 2005).

Recently, the number of pharmaceuticals approved in the United States (US) has been used as a direct measure of medical technology by Santerre (2011) and Willemé and Dumont (2015). Their results are mixed. Santerre (2011) found that the number of new molecular entities for the US and OECD countries reduce the growth in healthcare expenditure while Willemé and

Dumont (2015) found new molecules had an increasing effect on healthcare expenditures, whereas incremental innovations, measured by the total number of new drugs approved, had a negative effect.

Lastly, Willemé and Dumont (2015) also incorporate medical devices approved by the FDA as a proxy for medical technology, finding a net positive effect on healthcare expenditure. Other studies have used high-tech medical equipment such as CT scanners and MRI machines (Koenig et al., 2003; Hearle et al., 2003), and they found large variation in its effect on expenditure not only in magnitude of the effect but in sign. You and Okunade (2017) constructed two technology indexes (weighted and unweighted) based on medical devices (CT scanners, MRIs, lithotriptors, and radiation therapy equipment). Interestingly, when comparing effects of these indices with that from a residual approach the authors found a similar positive effect on health care expenditure for Australia.

This chapter includes Willemé and Dumont's proxies for technology (drugs and devices approved by the FDA) in the empirical analysis and incorporates three new proxies: number of approved drugs in Canada divided into two subgroups depending on the type of product, as well as number of completed clinical trials. The addition of approved drugs in Canada, a proxy conceptually similar to that of the US, aligns with the panel of Canadian provinces. The set of considered proxies incorporates drugs and devices (arguably the two main categories of medical technology) and clinical trials. They overcome some disadvantages of previously used approaches because they do not impose a rising trend; they incorporate innovations at a more advanced level than general R&D expenditures, implying a higher probability to achieve meaningful medical technologies ready to be used in the market; and they explicitly measure

innovation rather than adding technology to a set of other omitted variables (such as the residual approach). Overcoming these disadvantages is an important addition to the literature concerning the role of medical technology on healthcare expenditure. The data section below expands on the data sources and provides detailed definitions for the set of proxies used in this paper.

Other Healthcare Expenditure Drivers

While medical technology is a supply side driver of healthcare expenditure, affecting in various ways the production and delivery of healthcare, existing empirical studies on healthcare expenditure drivers have placed great attention on demand side factors. Particularly, one strand of the literature has emphasized that per capita income is the main driver of healthcare expenditure. Theoretically, a study has argued that as people get wealthier the marginal utility of consumption declines sharply and rational consumers will be willing to spend more on health in order to extend life and enjoy additional periods of utility (Hall and Jones, 2007). Empirical studies over the past 60 years have found mixed results regarding the effect of income on healthcare expenditures (a list of these studies and income elasticity estimates can be found in Baltagi, Lagravinese, Moscone, and Tosetti, 2017). In general, the magnitude of the income elasticity seems to vary with income levels. When comparing countries, poorer countries showed higher elasticity (Baltagi, Lagravinese, Moscone, and Tosetti, 2017). Similar results are found at a national level for income groups (Di Matteo, 2003).

A second strand of literature emphasizes aging and age structure of the population as a key driver of healthcare expenditure. An active debate in micro studies (such as those by Breyer, Lorenz and Niebel, 2015; Howdon and Rice, 2018; and Hazra, Rudisill and Gulliford, 2018) is

the relative importance of age versus proximity to death (red herring hypothesis) in explaining the effect of age on expenditures. An increasing proportion of elders in the population affects expenditure as older cohorts will use more healthcare services (with healthcare expenditure concentrated in the last few remaining years of life). However, empirical research that investigates the impact of aging on healthcare expenditure is mixed (Martin et al., 2011).

Another determinant of healthcare expenditure is the extent to which healthcare expenditures are financed by the government. On one hand, it is argued that greater public involvement in the market for healthcare may provide greater access to consumers at lower income levels, who are unable to pay for themselves; hence increasing the level of expenditure. On the other hand, if the government were to become a major player in the market for healthcare, it could lower the price for healthcare services, which would reduce individual healthcare expenditure (Pattnayak and Chadha, 2014). Empirical evidence provides conflicting results both in the magnitude and sign of the effect of the share of public spending on healthcare expenditures (Roberts, 1999).

A third, more limited, strand of the literature has focused on social determinants of health including income inequality, unemployment, and poverty (Rossen and Faroque, 2016). These factors have the potential to be detrimental to population health and, therefore, contribute to rising healthcare expenditures. Lifestyle variables such as smoking and dietary habits are included in an even fewer studies. For example, Willemé and Dumont (2015) incorporate average measures of body mass index.

The panel ECM incorporates medical technology and other determinants of healthcare expenditure for which consensus exists in the literature, and information was available. These

include income (measured by per capita GDP) and aging population effects (captured through the proportion of the population over 65 years of age). The public share of total healthcare expenditure is also included in the analysis to examine differences between countries that are above and below a threshold.

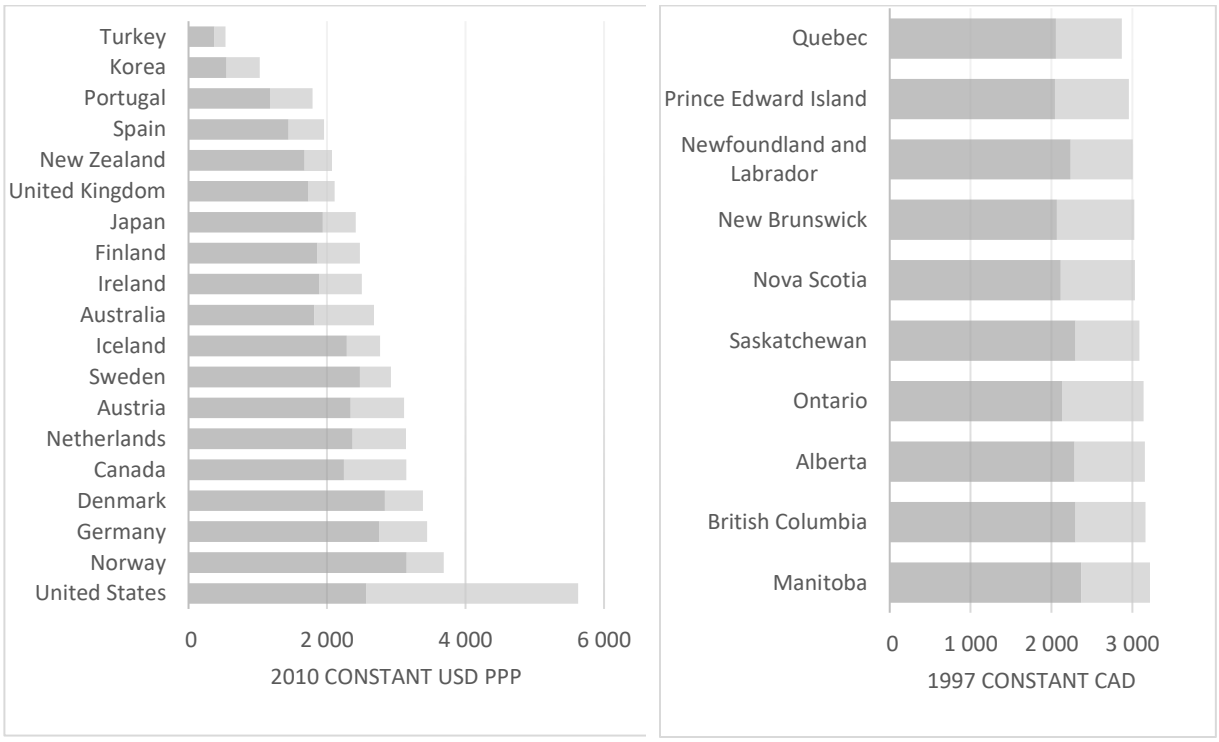
Data

Two panels are constructed to study the relationship between per capita healthcare expenditure and medical technology; one for OECD member countries and the other for Canadian provinces. The right panel of Figure 1 depicts average per capita healthcare expenditure for Canadian provinces over the period 1981-2016[1]. The Canadian data is displayed in 1997 constant CAD and the OECD data is displayed in 2010 constant USD purchasing power parity (PPP), as it is the data used to estimate the panel ECM. Total per capita expenditure among Canadian provinces is higher for Manitoba (around 3218 CAD) and lower for Quebec (2869 CAD). The province where public expenditure represents the lowest proportion of total expenditure is New Brunswick (around 68%) with the Canadian average being around 71% for the study period. The heterogeneity in provincial healthcare expenditure is partly due to the national health insurance program being administered autonomously through 13 provincial and territorial health insurance plans, with each being allowed to write policy and manage resources.

[1] Canada has a national health insurance program that aims to ensure "reasonable access to medically necessary hospital and physician services on a prepaid basis, without charges related to the provision of insured health services" (Health Canada, 2011), as enacted in the Canada Health Act in 1984. Canadian governments (federal and provincial) fund approximately 70% of the total national healthcare expenditure, with the remainder being paid through supplemental private insurance and out-of-pocket payments. For additional details on Canada's national insurance program, readers are referred to Martin et al. (2018).

This heterogeneity makes Canada an excellent candidate to compare results between highly-aggregated OECD macro-level data (country level) with that of a lower level of aggregation (provincial level). Canada's per capita healthcare expenditure is similar to many OECD member countries and is nearly identical to those of Austria and the Netherlands. Within the 19 countries included in the OECD panel, the US is a noticeable outlier with respect to healthcare expenditure.

Figure 1. Healthcare expenditure per capita by OECD member country (left) and by Canadian province (right), average 1981-2016.



Notes: Dark gray shading depicts the portion of healthcare expenditure that is public/government/compulsory. The light gray shading depicts the portion of healthcare expenditure that is private/out-of-pocket/voluntary. Healthcare expenditure for OECD member countries is in 2010 constant USD PPP from the Health Statistics Database, OECD iLibrary and expenditure for Canadian provinces is in constant 1997 CAD from the National Health Expenditure Database, CIHI.
CAD Canadian dollars, USD PPP U.S dollar purchasing power parity

Table 1 shows descriptive statistics for the variables used in both panels and separates healthcare expenditure into public and private expenditure. All variables are measured on an annual basis from 1981 to 2016. (The data are transformed by natural logarithm prior to conducting any empirical analysis.)

Table 1. Descriptive statistics for 1981 through 2016 (averaged by panel).

Variable	**OECD countries** in 2010 constant USD PPP (N = 19)	**Canadian provinces** in 1997 constant CAD (N = 10)
Public healthcare expenditure, per capita	1972.02 (51.16)	2178.94 (23.21)
Private healthcare expenditure, per capita	701.49 (93.66)	874.51 (35.11)
GDP, per capita	32138.05 (32.18)	28562.19 (24.61)
Population over 65 years old, % of total population	13.64 (27.31)	12.91 (18.33)

Notes: Coefficient of variation in parentheses. Please refer to the text for data sources.

CAD Canadian dollars, USD PPP U.S dollar purchasing power parity, GDP gross domestic product

Data for OECD member countries come from the OECD iLibrary Health Statistics (OECD, 2018c) and National Accounts databases (OECD, 2018a; 2018b). All OECD member countries with data on healthcare expenditure were included in the empirical analysis and include Australia, Austria, Canada, Denmark, Finland, Germany, Iceland, Ireland, Japan, Korea, the Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Turkey, United Kingdom, and the US. All excluded countries except Germany were missing many observations. Germany was missing an observation only for 1991, so it is included in the analysis with the missing

observation filled using linear interpolation. All variables are in constant PPP prices in 2010 USD.

Data for Canadian provinces comes from two sources. Health expenditure was collected from The National Health Expenditure Database (CIHI, 2020) while GDP and the proportion of the population over 65 years of age was collected from Statistics Canada (Statistics Canada, 2018a; 2018b). Data is available for all ten provinces and all variables are in constant 1997 CAD.

This brings us to the measure or proxy for medical technology. Seven potential proxies were compiled using data from three publicly-available sources. The original data for each of the medical technology proxies are in the form of a flow. They are converted to a stock variable using a 10% level of depreciation. Incorporating depreciation allows for obsolescence and/or revisions of existing technologies over time as new discoveries take place. However, it can be argued that technology represents the stock of medical knowledge and should not be discounted over time. Here, the decision to use a 10% depreciation for our technology proxies follows previous studies (Willemé and Dumont, 2015). As will be explained below, sensitivity of the results to additional depreciation rates will be investigated.

The first data source is the FDA (FDA, 2018a; 2018b; 2018c), which was used to create the four potential proxies originally defined by Willemé and Dumont (2015)[2]: new drug approvals (NDA), which includes prescription and over-the-counter human drugs and therapeutic biologicals currently approved for sale in the US; new molecular entities (NME), which includes only the subset of NDA with new chemical structures; medical device pre-market approvals

[2] We thank Willemé and Dumont for kindly sharing their data. The FDA has made changes to their drugs and medical devices reporting over the years, such as including new biologicals in the new drugs approvals. We have incorporated such changes, and updated the data series through to 2017.

(PMA), which are required for all Class III devices (those subjected to the strictest regulations); and medical device pre-market notifications (PMN), which are necessary for the remaining medical devices. The NDA proxy is further modified to exclude NME, which allows the simultaneous inclusion of both proxies in the empirical estimation.

The second data source is the National Library of Medicine at the National Institutes of Health (NIH, 2018), which contains a database on clinical trials conducted in 204 countries, including the US (studies conducted exclusively in the US constitute, on average, 34% of registered trials). A clinical trial is defined as, "a research study in which human volunteers are assigned to interventions (for example, a medical product, behavior, or procedure) based on a protocol (or plan) and are then evaluated for effects on biomedical or health outcomes" (U.S. National Library of Medicine, 2017). This database was used to extract a count of completed clinical trial recruitments (CTR) per time period[3], which is defined as the date that the last participant in a clinical study was examined or received an intervention to collect final data for the primary outcome measure. This is the first time CTR is used as a medical technology proxy in the healthcare expenditure literature. This global medical technology proxy is our preferred medical technology proxy because, in addition to drugs and devices, it includes advances in medical knowledge such as procedures and tests that are at an advanced stage of research. Specifically, as an average, 43% of the clinical trials are associated with drugs, 13% with devices, 11% with surgical procedures, and 33% with behavioral interventions.

[3] We gratefully acknowledge the discovery of this proxy through interdisciplinary dialogue with Dr. Tyler Grant who is the Director of Engineering at Lyndra Therapeutics Inc. and previously a postdoctoral fellow at Langer Lab at MIT.

The third data source is the Health Canada Drug Product Database (Health Canada, 2018), which provides information on drugs approved for use in Canada. This is a narrower proxy than CTR because it only includes drugs. This database was used to construct two proxies: newly-marketed drugs (NMD), and newly-marketed drugs with new active ingredients (NAI). NAI is a subset of NMD, which identifies the newly-marketed drugs which are highly innovative. A drug is considered highly innovative if it, "contains a medical ingredient not previously approved in a drug by the Minister and that is not a variation of a previously approved medicinal ingredient" (Health Canada, 2018). As with FDA proxies, NMD excludes NAI. We are the first to use NMD and NAI as medical technology proxies. Despite NMD and NAI being constructed based on newly-marketed drugs in Canada, this proxy is relevant beyond Canada because pharmaceutical companies are working to have their drugs approved for use in all OECD countries simultaneously so they can fully benefit from patent rights.

To facilitate replicability of this study and further use of our newly introduced proxies, data and codes for obtaining all three technology proxies are available in Rodriguez Llorian and Mann (2020).

Methods

A panel ECM following the DCCE-MG estimator by Chudik and Pesaran (2015) is used to investigate the relationship between medical technology and healthcare expenditure. Conventional panel data models assume identical slope coefficients, homogeneous impacts of common shocks across units of analysis, and stationary variables. But these assumptions will not likely hold in macro panels. To the extent of our knowledge, this paper is the first to apply the

DCCE-MG estimator by Chudik and Pesaran (2015) to study potential determinants of healthcare expenditure. Outside of health-related research, this model has been applied to investigate the relationship between growth and debt (Eberhardt and Presbitero, 2015), gross domestic product (GDP) and emissions (Lægreid and Povitkina, 2018; Xu, 2018), government and energy efficiency (Chang et al., 2018), and mortality and innovative activity (Herzer et al., 2020), amongst others.

The first step in the empirical analysis is to determine each series' order of integration. A series is integrated of order one if its first difference is stationary. Three tests are used to determine the order of integration of each variable in Table 1 using annual data from 1981–2016. The tests by Pesaran (2007) and Im, Pesaran and Shin (2003) have a null hypothesis of non-stationarity (for all panel members), while Hadri (2000) tests the null that all panels are stationary versus the alternative that at least one panel contains a unit root. Panel tests cannot be applied to the technology proxies because they do not vary by country or province. Thus, two univariate tests are used to determine the order of integration of each technology proxy. The test by Dickey and Fuller (1979, 1981) has a null hypothesis of a unit root, while KPSS (1992) tests the null of stationarity. The order of integration for the technology proxy is determined using monthly series since annual series from 1981 through 2016 are too short to apply univariate techniques. (Healthcare expenditure is only available at an annual frequency and limits the panel data analysis to an annual frequency.) Monthly data was chosen in lieu of simulating small sample critical values due to the finding by Pierse and Snell (1995) that temporal aggregation of data does not impact the local power of unit root tests by Dickey and Fuller (1979, 1981) in an asymptotic setting.

If the tests indicate the series are integrated of the same order, the next step is to test for cointegration. There are two main approaches to test for cointegration. The first is the so-called residual based test which collects the residuals from a regression and tests for stationarity. The second estimates an ECM and investigates whether the error correction term is significant. Here we follow the latter approach, with the significance of the error correction term from the panel ECM determining whether there exists a long-run relationship between the variables.

Specifically, the panel ECM estimated here following the DCCE-MG by Chudik and Pesaran (2015), is shown in equation (1). The DCCE-MG extends a traditional ECM by including cross sectional averages and lagged cross sectional averages in the right-hand side of the equation (F in equation 1), and by utilizing a mean group estimator (Pesaran and Smith, 1995). As will be further expanded below, the error correction specification and added cross sectional averages account for non-stationary and cross-sectional dependent data, while the MG estimator addresses parameter heterogeneity.

$$\Delta \ln (hce_{it}) = \alpha_i + \beta_{1i}[ln(hce_{i,t-1}) - \beta_{2i} \ln (gdp_{i,t-1}) - \beta_{3i} \ln (pop65_{i,t-1})) - \beta_{4i} \ln (tech_{\,t-1})] + \beta_{5i} \Delta \ln (gdp)_{i,t} + \beta_{6i} \Delta \ln (pop65)_{i,t} + \beta_7 \Delta \ln (tech)_{\,t} + F + \varepsilon_{it} \quad (1)$$

Where Δ is the first difference operator and F contains cross sectional averages as outlined below:

$$F = \beta_{8i} \Delta \ln (\overline{hce})_t + \beta_{9i} \Delta \ln (\overline{hce})_{t-1} + \beta_{10i} \Delta \ln (\overline{hce})_{t-2} + \beta_{11i} \ln (\overline{hce})_{t-1} + \beta_{12i} \Delta \ln (\overline{gdp})_t + \beta_{13i} \Delta \ln (\overline{gdp})_{t-1} + \beta_{14i} \Delta \ln (\overline{gdp})_{t-2} + \beta_{15i} \ln (\overline{gdp})_{t-1} + \beta_{16i} \Delta \ln (\overline{pop65})_t + \beta_{17i} \Delta \ln (\overline{pop65})_{t-1} + \beta_{19i} \Delta \ln (\overline{gdp65})_{t-2} + \beta_{20i} \ln (\overline{gdp65})_{t-1} \quad (2)$$

In the above equations hce is the per capita healthcare expenditure, gdp is the per capita income, $pop65$ is the proportion of the population over 65 years of age, and $tech$ is the medical

technology proxy – all as logarithms. The lag length of cross sectional averages, as suggested by Chudik and Pesaran (2015), is $p = int\left(T^{\frac{1}{3}}\right)$, in this case being equivalent to 2 lags as shown in equation (2).

The error correction coefficient (EC), β_{1i}, measures the speed of adjustment to the long-run equilibrium. If $EC = 0$, there is no error correction, meaning the variables do not follow a long-run relationship. If $EC \neq 0$, the variables under study are cointegrated. Furthermore, the expression in squared brackets in equation (1) contains the long-run effects, which are the focus of our analysis. This long-run parameters β_{ki} for $k = 2, 3, 4$ are calculated by dividing the value of the lagged level variable coefficient with the value of the error correction term (i.e β_{ki}/β_{1i}) (Eberhardt and Presbitero, 2015)[4]. The coefficient estimates for differenced variables (Δ) are interpreted as short-run effects.

The subscript *i* on the coefficients in equation (1) indicates that the model recognizes heterogeneity in observables by adding country-specific (or province) intercepts and slopes on the observable regressors[5]. In practice, this translates into using a mean group estimator (Pesaran and Smith, 1995) which estimates separate time series regressions for each country (province) and then averages the individual country coefficients. This heterogeneity is fundamental in our analysis. The autonomy of countries, or provincial governments (for the Canadian case), in managing, funding and delivering healthcare implies that the effects on healthcare expenditure are likely to vary across units of analysis. The heterogeneous coefficients also serve as a

[4] Details for the Stata code used for the empirical estimation (xtmg) can be found in Eberhardt (2012).

[5] Note that $tech$ does not have a subscript *i* since all technology proxies are common across units of analysis (provinces and countries respectively), making the subscript redundant.

comparison for other widely-used methods that incorporate a homogeneous slope, such as pooled ordinary least squares, two-way fixed effects, and the Arellano and Bond estimator. If the effect of the different determinants on healthcare expenditure is heterogeneous, a model with homogeneous slopes might provide misleading policy recommendations (Blomqvist and Carter, 1997).

Equation (1) also incorporates cross-section averages of the dependent and independent variables as additional regressors (*F*). These serve to control for unobserved common factors (i.e. exogenous shocks on healthcare expenditure) which are allowed to vary across units and over time (Pesaran, 2006). Unobserved common factors (such as medical technology advances, epidemiological changes, shifts in patients' preferences, or fluctuations in the economic cycle) may induce interdependency between units, or cross-sectional dependence, and derive inconsistent estimates if they are correlated with the explanatory variables (Phillips and Sul, 2003; Andrews, 2005)[6]. Traditional approaches account for common factors by demeaning the data or including time dummies, therefore assuming that the response to common factors is homogeneous across units of analysis. This assumption is likely violated in this context since countries differ quite markedly in the rate by which they adopt medical innovations. If the assumption of homogeneity is not valid, demeaning the panel or using time dummies usually does not eliminate cross-sectional dependence. The common correlated effect (CCE) procedure used here allows for heterogeneous effects of common factors.

[6] Since the medical technology proxies are common for all units in the panel, they should be considered as an observed common factor in our model (as opposed to the cross-section averages of all other model variables, which capture unobserved common factors)

Furthermore, the method also allows for the unobservable common factors to be correlated with the regressors. In the healthcare expenditure case, it is reasonable to assume that shocks in medical technology, for example, will be correlated with some of the observable factors included in the model, such as income. The CCE model followed here allows for correlation between the observables and the common factors. This way, medical technology advances affect healthcare expenditure directly through the observable proxy for technology, and the unobservable common factor, but also indirectly through its potential indirect relationship with other regressors. Another advantage of the approach is that it relaxes the assumption of strict exogeneity for the observables, allowing also feedback among income, aging population and medical technology. Chudik and Pesaran (2015) showed that, once augmented with a sufficient number of lagged cross-sectional averages, the DCCE-MG estimator performs well with weakly exogenous regressors.

Results

Results from the panel unit root and stationarity tests for OECD member countries and Canadian provinces are reported in Table 2. Together, the tests indicate that it is reasonable to treat the variables as first-difference stationary for both OECD member countries and Canadian provinces. We also tested for cross-section dependence using the test by Pesaran (2004). The results are shown in the last column of Table 2 and find the variables are subject to cross-sectional dependence.

Table 2. Results from panel unit root, stationarity and Pesaran (2004) tests.

	Pesaran (2007)		Hadri (2000)	Im-Pesaran and Chin (2003)	Pesaran (2004)
	Number of lags				
OECD	1	2			
HCE	0.39	1.24	35.56***	0.85	75.84***
GDP	-0.32	0.81	48.32***	1.88	75.13***
POP65	-0.21	1.46	45.42***	0.64	60.30***
Canada					
HCE	-2.67***	-3.31***	25.44***	-1.14	39.48***
GDP	-1.59*	0.57	20.46***	0.78	39.00***
POP65	-0.85	2.41	39.53***	-0.42	37.02***

Note: All variables are in their logarithmic transformation. The Pesaran (2004) test has a null hypothesis of cross-section independence. Significance at α = 0.01, 0.05, and 0.1 is denoted by ***, **, and *, respectively.

HCE per capita healthcare expenditure, GDP per capita income, POP65 proportion of the population over 65 years of age

Results from univariate unit root and stationarity tests for the seven medical technology proxies are reported in Table 3. The results vary widely between the proxies, with some being I(0), others being I(1), and still others being fractionally integrated or even I(2). The only proxies for which it is reasonable to treat as I(1) are PMA, CTR, and NMD, which provides an additional advantage for our new medical technology proxies CTR and NMD.

Table 3. Results from univariate unit root and stationarity tests for technology proxies.

Proxy	**ADF Unit Root Test**		**KPSS Test**	
	Level	Δ	Level	Δ
NDA (T = 421)	-4.086***	N/A	0.110	N/A
NME (T = 421)	-4.846***	N/A	0.313***	0.094
PMA (T = 421)	-3.145*	-20.746***	0.206**	0.072
PMN (T = 421)	-3.445**	N/A	0.365***	0.363
CTR (T = 301)	0.732	-15.208***	0.336***	0.571**
NMD (T = 229)	-2.773	-13.883***	0.245***	0.130
NAI (T = 229)	-5.568***	N/A	0.204**	0.150

Notes: All results in this table incorporate monthly data ending in 2016. Unit root and KPSS tests on level data include both a constant and trend as deterministic components and the differenced data (Δ) includes only a trend. If the null hypothesis for the unit root test is rejected for the level data it is not necessary to conduct the test on the Δ data. Similarly, if the null hypothesis for the KPSS is not rejected for the level data it is not necessary to conduct the test on the Δ data. The lag length for the ADF unit root test selected from a maximum of $T^{1/3}$ by minimizing the BIC. Maximum lag truncation for the KPSS test for stationarity is selected as $12(T/100)^{0.25}$. The length of the data series ranges from T = 229 through 421. Significance at α = 0.01, 0.05, and 0.1 is denoted by ***, **, and *, respectively.

ADF Augmented Dickey Fuller unit root test, KPSS Kwiatkowski, Phillips, Schmidt, and Shin test, NDA new drug approvals, NME new molecular entities, PMA medical device pre-market approvals, PMN medical device pre-market notifications, CTR clinical trial recruitments, NMD newly-marketed drugs, NAI newly-marketed drugs with new active ingredients.

We continue by estimating the panel ECM with various combinations of the three I(1) proxies. Table 4 contains results for the estimation of the ECM in four scenarios. Specifically, results are reported for OECD countries and Canadian provinces separately; and with clinical trials (CTR) being the only proxy for medical technology, versus drugs and devices (NMD and PMA) simultaneously accounting for medical technology advancements. Two models are included for each of these four combinations: the first only incorporates GDP and technology proxy; and the second adds POP65. The first column presents estimations without any technology variables. Investigating the coefficient estimates from the different models will also inform whether coefficients are being impacted by having too many variables for a cointegration framework. Diagnostic tests of the four scenarios in Table 4, including the cross-sectional dependence test by Pesaran (2004) and the root mean squared error, confirm the effectiveness of our estimates.

Table 4. Results from error correction model.

Panel A. *OECD Panel*

	No technology variables	**Clinical Trials as proxy for technology**		**Drugs and devices as proxy for technology**	
		Model 1	Model 2	Model 1	Model 2
EC	-0.591 [0.058]***	-0.574 [0.056]***	-0.728 [0.044]***	-0.608 [0.051]***	-0.661 [0.086]***
ln(GDP)	0.619 [0.269]**	0.5313 [0.1728]***	0.4006 [0.1764]**	0.5573 [0.1945]***	0.3092 [0.2954]
ln(POP65)	-0.773 [0.4888]		-0.0054 [0.578]		-0.5743 [0.6276]
ln(CTR)		-0.0085 [0.0298]	0.0036 [0.0264]	-	-
ln(NMD)				0.0546 [0.0772]	-0.0008 [0.0812]
ln(PMA)				0.0054 [0.092]	-0.0611 [0.0839]
RMSE	0.0175	0.0185	0.014	0.0186	0.014
CD test	-2.0712 (0.038)	-2.7722 (0.006)	-1.6916 (0.091)	-2.6099 (0.009)	-1.2943 (0.196)
Obs	627	608	608	627	627

Panel B. *Canadian Panel*

	No technology variables	**Clinical Trials as proxy for technology**		**Drugs and devices as proxy for technology**	
		Model 1	Model 2	Model 1	Model 2
EC	-0.945 [0.074]***	-0.72 [0.087]***	-1.139 [0.085]***	-0.698 [0.092]***	-1.05 [0.117]***
ln(GDP)	0.0834 [0.1495]	0.1554 [0.1217]	0.1512 [0.1071]	0.137 [0.2105]	-0.137 [0.1565]
ln(POP65)	-0.3116 [0.4141]		0.4919 [0.6089]		-1.0682 [0.9286]
ln(CTR)		-0.0042 [0.0191]	0.005 [0.0193]		
ln(NMD)				-0.0123 [0.0938]	-0.1945 [0.094]**

ln(PMA)				-0.0453 [0.036]	0.006 [0.0703]
RMSE	0.0099	0.0121	0.0084	0.0123	0.0084
CD test	-2.7094 (0.007)	-3.6171 (0.00)	-1.7862 (0.074)	-3.2773 (0.001)	-2.9686 (0.003)
Obs	330	320	320	330	330

Notes: The dependent variable for all models is the first difference of total healthcare expenditure, expressed as logs. Other variables are included in the estimated equations as stated in equations 1 and 2. We present only the long-run coefficients, which are robust mean estimates of the heterogeneous models. Estimations for the complete ECM are available on request. Standard errors, in square brackets, are constructed following Pesaran and Smith (1995).
All estimations are weighted averages (outlier robust). The depreciation rate used for all technology variables is 10%. RMSE is the root mean square error, and the CD tests report a Pesaran (2004) test with a null of cross-section independence, with p values in parentheses. All models are augmented with country-specific linear trends.
Significance at α = 0.01, 0.05, and 0.1 is denoted by ***, **, and *, respectively.
HCE per capita healthcare expenditure, GDP per capita income, POP65 proportion of the population over 65 years of age, CTR clinical trial recruitments, NMD newly-marketed drugs, PMA medical device pre-market approvals.

The first important result relates to the value of the error correction term (EC) which determines whether the series are cointegrated. In all models, there is statistically significant evidence of error correction at a 0.01 level of significance, and therefore cointegration. The existence of a long-run relationship between medical technology and healthcare expenditure implies that, in the presence of shocks, the system adjusts to restore the long-run equilibrium. The speed of adjustment toward this equilibrium varies across models. Estimations reveal a higher speed of adjustment for the Canadian panel, and for the model with drugs and devices as proxies for medical technology.

Looking at the OECD panel, long run coefficients for income range from 0.31 to 0.56, with the exception of the model that excludes technology whose coefficient is 0.62. These findings are consistent with previous studies in that income explains much of the variation in healthcare expenditure, with higher values in the absence of a technology proxy. Particularly,

Baltagi et al. (2017) used a CCE-MG estimator without a technology proxy and estimate elasticity for high income countries to be 0.45; while Willemé and Dumont (2015) used a fixed effects model and estimate an elasticity close to one for OECD countries. The GDP coefficients for the Canadian panel are not statistically significant and, similar to the OECD panel, the addition of the proportion of the population over 65 years of age results in a greater effect of GDP. Estimates for the OECD panel also show a positive and significant effect for the coefficient accompanying $\Delta \ln(gdp)$ between 0.28 and 0.45, indicating that health spending also reacts to short run variations in GDP (Table 4 only shows the long-run coefficients). OECD countries in general have advanced and organized healthcare systems that are capable of adjusting their health spending to react to short-run variations in income levels.

As for the technology proxies, new marketed drugs (NMD) was found to have a negative and statistically significant effect (-0.20) for the panel of Canadian provinces (model 2 Panel B). This result is consistent with that found by Willemé and Dumont (2015) in that new total drugs appear to reduce healthcare expenditures (the authors found an elasticity between -0.36 and -0.48 for new drugs approved by the FDA). One possible explanation is that an incremental drug innovation lowers the use of other medical interventions and avoids additional procedures, resulting in a net negative effect on expenditure (Santerre, 2011). This suggests that policies of cost containment should carefully take into account the effect that new drugs might have in substituting for other more expensive alternatives, with reimbursement decisions evaluated alongside other medical expenses. Finding the technology proxy based on Canadian data is only statistically significant for the Canadian panel also hints at the potential benefits associated with country-specific approval data. The rest of the long- run coefficients for the technology variables are not statistically significant. This does not necessarily imply the absence of impact, rather

points to effects cancelling out on average since the specification allows for heterogeneous parameters. Here, the impact of different determinants on healthcare expenditure differs substantially across units of analysis, thus a focus on the average relation may be misleading for policy adoption in individual countries (provinces).

Appendix A.2 shows underlying group-specific regression results. For those countries for which the CTR variable is statistically significant (Australia, Canada, Denmark, Iceland, Korea, New Zealand, Norway, Portugal and Spain), its effect is mostly negative (long run coefficients between -016 and -0.09). Marked differences are found in the effect of drugs and devices on expenditure across countries and provinces. There is not a straightforward explanation for this result but possible explanations include structural differences in healthcare organization, regulation, financing as well as provision of services. Specifically, each country adopts new technologies differently which could lead to an expansion of treatment, a substitute for a previously more expensive service, or a combination. Given the observed heterogeneity, empirical results should be taken with caution.

One perplexing finding from the OECD panel that incorporates drugs and devices to proxy medical technology is the income variable becomes statistically insignificant after adding covariates to the ECM. A possible explanation is that additional covariates may result in more than one cointegrating relationship. (Herzer et al., 2020). The effect on the estimated long-run coefficients is still uncertain in the panel time series literature. Nevertheless, as outlined above, strong and robust evidence of error correction is found across all specified models.

Appendix A.3 presents results for an incorrect application of the fixed effects model, which constrains both the long and short run coefficients to be the same across countries

(provinces), and does not include cross sectional averages. (Reasons why this is an 'incorrect application' are detailed within the methodology section.) The estimations give conflicting results with the DCCE-MG estimator, with most determinants being statistically significant including technology proxies and GDP. It is important to note is that results for the fixed effects model show evidence of cross-sectional dependence, as can be seen by the CD test. The implication of such marked differences with the fixed effect model is that evidence from conventional methods regarding the relationship between healthcare expenditure and additional drivers should interpreted with extreme caution.

Robustness checks

The robustness of the results are investigated first with respect to the inclusion / exclusion of the US in the panel of OECD countries due to its extreme healthcare expenditures as shown in Figure 1. Then, with respect to the depreciation rate for the technology measure. Table 5 replicates Table 4 (panel A) without the US as part of the panel of OECD countries. Results are robust in terms of the existence of cointegration for all models. Long-run coefficients are similar not only in significance but also in magnitude. The results are also robust to changes in the depreciation rate for the technology variables from 10% to 5% as shown in Table 6.

Table 5. Robustness to excluding US in panel of OECD countries

	Clinical Trials as proxy for technology		**Drugs and devices as proxy for technology**	
	Model 1	Model 2	Model 1	Model 2
EC	-0.602 [0.054]***	-0.745 [0.043]***	-0.627 [0.045]***	-0.698 [0.083]***
ln(GDP)	0.5024 [0.1842]***	0.4258 [0.1843]**	0.6133 [0.2005]***	0.3371 [0.3169]
ln(POP65)		-0.0552		-0.3515

		[0.551]		[0.6339]
ln(CTR)	-0.0077 [0.0306]	0.002 [0.0248]		
ln(NMD)			0.0604 [0.0764]	0.0031 [0.0822]
ln(PMA)			0.0215 [0.0903]	-0.0641 [0.0944]
RMSE	0.0188	0.0143	0.019	0.0141
CD test	-2.876 (0.004)	-2.0102 (0.044)	-3.0169 (0.003)	-1.8537 (0.064)
Obs	576	576	594	594

Notes: The dependent variable for all models is the first difference of total healthcare expenditure, expressed as logs. Other variables are included in the estimated equations as stated in equations 1 and 2. We present only the long-run coefficients, which are robust mean estimates of the heterogeneous models. Estimations for the complete ECM are available on request. Standard errors, in square brackets, are constructed following Pesaran and Smith (1995). All estimations are weighted averages (outlier robust). The depreciation rate used for all technology variables is 10%. RMSE is the root mean square error, and the CD tests report a Pesaran (2004) test with a null of cross-section independence, with p values in parentheses. Significance at α = 0.01, 0.05, and 0.1 is denoted by ***, **, and *, respectively.

Table 6. Robustness to changing depreciation rates to 5%

Panel A. *OECD Panel*

	Clinical Trial as proxy for technology		**Drugs and devices as proxy for technology**	
	Model 1	Model 2	Model 1	Model 2
EC	-0.579 [0.055]***	-0.743 [0.044]***	-0.654 [0.057]***	-0.699 [[0.089]***
ln(GDP)	0.5186 [0.1672]***	0.4046 [0.1742]**	0.5157 [0.1871]***	0.2913 [0.285]
ln(POP65)		0.0302 [0.573]		-0.416 [0.5481]
ln(CTR)	-0.0079 [0.03]	0.0016 [0.0263]		
ln(NMD)			0.0722 [0.0956]	0.0352 [0.1036]
ln(PMA)			0.0212 [0.1033]	-0.1134 [0.1251]
RMSE	0.0185	0.014	0.0182	0.0138

CD test	-2.7904 (0.005)	-1.6088 (0.108)	-2.7011 (0.007)	-1.4529 (0.146)
Obs	608	608	627	627

***Panel B**. Canadian Panel*

	Clinical Trial as proxy for technology		**Drugs and devices as proxy for technology**	
	Model 1	Model 2	Model 1	Model 2
EC	-0.718 [0.087]***	-1.145 [[0.083]***	-0.73 [0.095]***	-1.062 [0.131]***
ln(GDP)	0.1583 [0.1225]	0.1506 [0.105]	0.1332 [0.2078]	-0.1035 [0.1181]
ln(POP65)		0.4893 [0.6277]		-1.3793 [0.8266]
ln(CTR)	-0.0044 [0.0189]	0.0046 [0.019]		
ln(NMD)			0.0011 [0.1173]	-0.1166 [0.1317]
ln(PMA)			-0.0538 [0.0429]	0.0209 [0.121]
RMSE	0.0121	0.0084	0.0121	0.0083
CD test	-3.6136 (0.000)	-1.8002 (0.072)	-2.9377 (0.003)	-2.7513 (0.006)
Obs	320	320	330	330

Notes: The dependent variable for all models is the first difference of total healthcare expenditure, expressed as logs. Other variables are included in the estimated equations as stated in equations 1 and 2. We present only the long-run coefficients, which are robust mean estimates of the heterogeneous models. Estimations for the complete ECM are available on request. Standard errors, in square brackets, are constructed following Pesaran and Smith (1995). All estimations are weighted averages (outlier robust). RMSE is the root mean square error, and the CD tests report a Pesaran (2004) test with a null of cross-section independence, with p values in parentheses. Significance at α = 0.01, 0.05, and 0.1 is denoted by ***, **, and *, respectively.

Robustness of the results is also checked by modifying the number of OECD countries in the sample. In the main estimations, a group of countries was excluded due to missing data for the period 1981-2016. Table 7 shows estimations for a larger number of OECD countries using a

shorter period between 1991 to 2016. The results show estimations for 27 countries (adding now Belgium, Czech Republic, France, Greece, Hungary, Italy, Poland, and Switzerland), and are consistent with table 4.

Table 7. Robustness to including 27 OECD countries, 1991-2017. Model 1.

	Clinical Trial as proxy for technology	**Drugs and devices as proxy for technology**
EC	-0.828*** [0.056]	-0.952*** [0.077]
ln(GDP)	0.4556 [0.3155]	0.5599 [0.3017]*
ln(POP65)		
ln(CTR)	0.0433 [0.0516]	
ln(NMD)		-0.0494 [0.0709]
ln(PMA)		0.0575 [0.1182]
RMSE	0.0137	0.0103
CD test	-2.3938 (0.017)	-0.2475 (0.804)
Obs	621	621

Notes: The dependent variable for all models is the first difference of total healthcare expenditure, expressed as logs. Other variables are included in the estimated equations as stated in equations 1 and 2. We present only the long-run coefficients, which are robust mean estimates of the heterogeneous models. Estimations for the complete ECM are available on request. Standard errors, in square brackets, are constructed following Pesaran and Smith (1995). All estimations are weighted averages (outlier robust). RMSE is the root mean square error, and the CD tests report a Pesaran (2004) test with a null of cross-section independence, with p values in parentheses. Significance at α = 0.01, 0.05, and 0.1 is denoted by ***, **, and *, respectively.

Lastly, table 8 presents results separating the sample of OECD countries according to the public share of total healthcare expenditure (Pub). Results are presented for a threshold of 70%. Countries with a public share of total healthcare expenditure under 70% are Australia, Korea, Portugal, Turkey, and US. As expected, estimations show that those countries with a proportion

over 70% showed greater elasticity of income. Interestingly, some of the proxies for technology are statistically significant for those countries with a smaller presence of the government in healthcare financing for the simpler model (model 1). While clinical trials are found to decrease expenditure, new devices showed the opposite effect.

Table 8. Robustness to separate countries using a 70% threshold for public share of total healthcare expenditure

Panel A. *OECD Panel – CTR as proxy for technology*

	Model 1 Pub<70	**Model 1 Pub>70**	**Model 2 Pub<70**	**Model 2 Pub>70**
EC	-0.515 [0.163]***	-0.623 [0.068]***	-0.588 [0.160]***	-0.851 [0.067]***
ln(GDP)	0.4278 [0.3451]	0.6091 [0.2075]***	0.31 [0.6142]	0.547 [0.208]***
ln(POP65)			0.0967 [0.2143]	0.147 [0.4847]
ln(CTR)	-0.1106 [0.0523]***	0.001 [0.0262]	-0.0223 [0.1019]	0.0163 [0.0273]
RMSE	0.0185	0.0162	0.0155	0.0125
CD test	-2.0184 (0.044)	-2.8294 (0.005)	-2.2228 (0.026)	-1.9924 (0.046)
Obs	160	448	160	448

Panel B. *OECD Panel – NMD and PMA as proxy for technology*

	Model 1 Pub<70	**Model 1 Pub>70**	**Model 2 Pub<70**	**Model 2 Pub>70**
EC	-0.586 [0.187]***	-0.576 [0.044]***	-0.656 [0.144]***	-0.724 [0.086]***
ln(GDP)	0.2039 [0.3546]	0.7923 [0.3479]**	0.1867 [0.0742]***	0.483 [0.201]**
ln(POP65)			-0.5858 [0.6316]	-0.3273 [0.8322]
ln(NMD)	0.1858 [0.3046]	-0.039 [0.0671]	0.1529 [0.3061]	-0.0217 [0.1244]

ln(PMA)	0.0926 [0.0436]***	-0.0145 [0.1079]	0.0236 [0.0807]	-0.0813 [0.1516]
RMSE	0.0201	0.0154	0.0178	0.0113
CD test	-1.3467 (0.178)	-2.6886 (0.007)	-1.6035 (0.109)	-2.803 (0.005)
Obs	165	462	165	462

Notes: The dependent variable for all models is the first difference of total healthcare expenditure, expressed as logs. Other variables are included in the estimated equations as stated in equations 1 and 2. We present only the long-run coefficients, which are robust mean estimates of the heterogeneous models. Estimations for the complete ECM are available on request. Standard errors, in square brackets, are constructed following Pesaran and Smith (1995). All estimations are weighted averages (outlier robust). RMSE is the root mean square error, and the CD tests report a Pesaran (2004) test with a null of cross-section independence, with p values in parentheses. Significance at α = 0.01, 0.05, and 0.1 is denoted by ***, **, and *, respectively.

Remarks

This paper investigates the effect of medical technology on healthcare expenditure for two panels at different levels of aggregation: OECD countries and Canadian provinces, during the period 1981-2016. It follows previous work by isolating medical technology as a driver of healthcare expenditure in a panel framework. This paper contributes to existing literature by introducing three new proxies for medical technology. The new proxies are conceptually attractive and add depth to existing proxies by explicitly measuring innovation without assuming a monotonically increasing trend. While CTR successfully represents advanced developments in medical knowledge, including not only drugs and devices but also procedures and tests, NMD and NAI capture new ready to use technology. The time series properties of both the new and existing proxies are rigorously analyzed, which provides guidance on its inclusion in time series analysis. The new proxies are relevant for empirical researchers interested in determining drivers of healthcare expenditure and those interested in assessing medical technology across diciplines.

The proxies are incorporated into a novel dynamic approach to model the relationship between technology and healthcare expenditure, which addresses issues of cross-sectional dependence, heterogeneity and endogeneity. Results for both OECD countries and Canadian provinces corroborate previous empirical evidence that healthcare expenditure and medical technology are tied together by a long-run relationship. Results are robust to changes in the depreciation rate, the inclusion/exclusion of the US, the extension of the panel to 27 countries (at the expense of a reduced time dimention), and to different thresholds of the public proportion of expenditure.

Estimations also show that commonly used empirical methods might have overestimated the average impact of technology on healthcare expenditures. Specifically, incorporating heterogeneity and controlling for cross-sectional dependence and endogeneity showed that comparing country (province) specific coefficients might be more insightful for a policy-relevant and informed discussion. Here, findings are mixed with respect to magnitude and direction for the technology-healthcare expenditure nexus, with medical technology decreasing healthcare expenditure for some countries (provinces) but not for others. Among the proxies included, while new drugs and devices measure the stock of approved medical technology in specific countries (Canada and the U.S respectively), clinical trials incorporates the availability of new innovations in over 200 countries. This hints that future studies could greatly benefit from quantifying more explicitly not only approved medical technology, but also the regulatory process for this new technology which is a component of the diffusion rate. The assumption made here is that approved medical technologies, after some time lag, will be used on the ground by doctors; therefore representing changes in treatment decisions. But each country (province) adopts new medical technology at very different paces. Consequently, the impact of medical technology on

healthcare expenditure could be more rigorously explored by accounting for the process of regulation that mediates between a medical innovation being approved and used in each country (province).

Finally, the diversity in the effect of technology across OECD countries and Canadian provinces suggests three fruitful areas for future study. One area is to incorporate national approval data. Another is to disaggregate expenditures into categories such as pharmaceutical, physicians, and hospital expenditures. And, a third is to incorporate changes in medical outcomes (not captured by the expenditure data). Studying whether some of the technologies that increase healthcare expenditure also improve medical outcomes and quality of life will provide great insights into the technology-healthcare expenditure nexus.

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Chapter 2. Healthcare Use and The Telehealth Program in Manitoba: An Evaluation using Linked Administrative Data

Introduction

Technological advances in recent decades have influenced the way healthcare services are delivered. The term 'telemedicine' has changed over the years from a mere service characterizing "the practice of medicine without the usual physician-patients confrontation …via interactive audio-video communication system" (Bird, 1971), to one including "the delivery of health care services, where distance is a critical factor, by all health care professionals using information and communication technologies for the exchange of valid information for diagnosis, treatment and prevention of disease and injuries, research and evaluation…" (WHO, 2010). 'Telehealth' is closely related to telemedicine. Telemedicine tends to be used exclusively in a clinical context, whereas telehealth includes all remote interactions to improve patient care, including non-clinical events such as administrative meetings and medical education. In other cases, telemedicine is used exclusively for services delivered by physicians. In this paper, we use the term telemedicine, except when referring to specific program's names.

Bashshur, Shannon, Krupinski, & Grigsby (2011) described a taxonomy of telemedicine with three main areas: technological configurations, functions that are performed, and specific applications. This classification highlights the heterogeneity of telemedicine interventions, and is useful for research and policy evaluations. Careful classification of a given telemedicine program within this framework contributes to a better understanding of the field, and adds rigor and comparability across telemedicine studies.

The first taxonomic area has three sub-areas: synchronicity, which incorporates timing (real-time or synchronous consultations, versus those conducted in store-and-forward or asynchronous fashion), as well as technology type (videoconference, remote monitoring and other forms of interactive health communications); network design type (internet, social networks, and virtual private networks); and connectivity (wired or wireless). For the second area, the core functions that are performed comprise consultations between physicians and patients, as well as physician-to-physician, such as for diagnosis, monitoring or mentoring. In the third area, the specific applications found in telemedicine interventions include medical specialties as well as sub-specializations based on disease entities, sites of care (such as intensive care unit, outpatient settings, and emergency rooms), and treatment modalities (e.g. rehabilitation and pharmacy). All of these overlap, and are closely interconnected.

Telemedicine as an innovative system of care has the potential to solve some acute problems in healthcare, including accessibility through expanding the reach of treatment, and reduced costs for providers and patients. Proponents also claim that telemedicine could support improved treatment and better health outcomes, not only through the provision of care previously undeliverable, but also by improving communication between primary care and specialists (Hjelm, 2005), and because of telemedicine's suitability for certain conditions and age groups. Some mental health patients, for example, could benefit from care received at home (Pruitt et al., 2014). Other research shows how greater engagement can be achieved through electronic health interactions targeted at millennials (CTeL, 2018; Hansen & Okuda, 2018; Powers, 2018). Despite the many claimed benefits, clear demonstration of telemedicine's effects, other than increased access to care, have remained elusive (CADTH, 2016; Ekeland, Bowes, and Flottorp, 2010; Shigekawa et al., 2018; Wootton, 2012; McLean et al., 2013).

Specifically, although existent studies suggest that telemedicine affects the delivery of healthcare services, the idea, mostly put forward by policy makers, that virtual consultations might replace a more expensive face-to-face encounter has not been supported by recent research. Instead, virtual visits appear to add to the volume of face-to-face visits (Ashwood et al., 2017). Beyond visits to physicians, other indicators of healthcare use have been studied, including hospitalizations and/or length of stay (Kalankesh et al., 2016), emergency department visits (Pekmezaris et al., 2018), and medication adherence (Hommel et al., 2013), with mixed results found across indicators and studies. A recent literature review suggests the relation between telemedicine and the use of other care services varies widely depending on patient demographics, service modality, and the quality of the studies (Shigekawa et al., 2018). Consequently, conclusions cannot be readily drawn regarding the effects of telemedicine on utilization of health services.

This paper empirically investigates whether telemedicine changes the utilization patterns of patients in the province of Manitoba, where the MBTelehealth program (MBT) is responsible for the province's telehealth services. Manitoba covers 649,950 square kilometers, and is well suited to benefit from the use of telemedicine, given that around 40% of its population lives in non-metropolitan areas (Rural Development Institute, 2014). The MBT program is mainly aimed at improving access to healthcare through communication technologies, as well as reducing travel and associated costs. Interactions between patients and providers take place using video conference, either through room-based equipment or from a provider's computer or mobile device. The option of e-Consult (store-and-forward) allows providers to consult, ask questions and send digital images to a specialist without the patient having to travel (MBT, 2018).

The type of care provided through telemedicine during the studied period could be categorized under a first generation of virtual care practices. The model, as studied here, is limited to using healthcare sites spread throughout the province to deliver the medical consult, as well as store and forward features (as outlined above). The number of these sites rose in Manitoba from 21 in 2001 to 148 by 2015 (Nyhof, 2015) and live clinical telemedicine sessions increased from 6,959 in 2010 to 16,085 in 2014 (COACH, 2015). Understanding the particularities of each model of care delivered virtually is essential for future comparisons or extrapolations of this study.

A previous study in Manitoba (MBT, 2011) showed high satisfaction with the service and a perceived increase in access. That study estimated a $1 million annual cost saving in staff time, including travel, and a $2.6 million saving for patients and their families. Likewise, other studies have explored cost-effectiveness and patient satisfaction for specific telemedicine applications in Manitoba, with positive net health-system savings (see Kanjee et al., 2016 for an application to tele-ophthalmology; and Ellis et al., 2019 for a case of pediatric concussion patients living in northern communities). However, no study to date has assessed the overall effect of telemedicine in Manitoba on utilization outcomes. This limitation can now be overcome with the linkable administrative data from the Manitoba Population Research Data Repository (Repository), housed at the Manitoba Centre for Health Policy (MCHP).

Using a propensity-weighted regression model four utilization outcomes are compared between a group of telemedicine users and another group of non-users. Results indicate that, compared to non-users, telemedicine patients have higher in-person visits (with primary care physicians and specialists), as well as more hospitalizations. The results are robust to

adjustments for distance, regions and chronic conditions, which adds to the strength of the findings. However, for those patients who show a higher intensity of telemedicine use (meaning frequent virtual encounters with a specialist) telemedicine resulted in a decrease of in-person visits. The paper further discusses potential explanations and policy implications of this findings.

Data

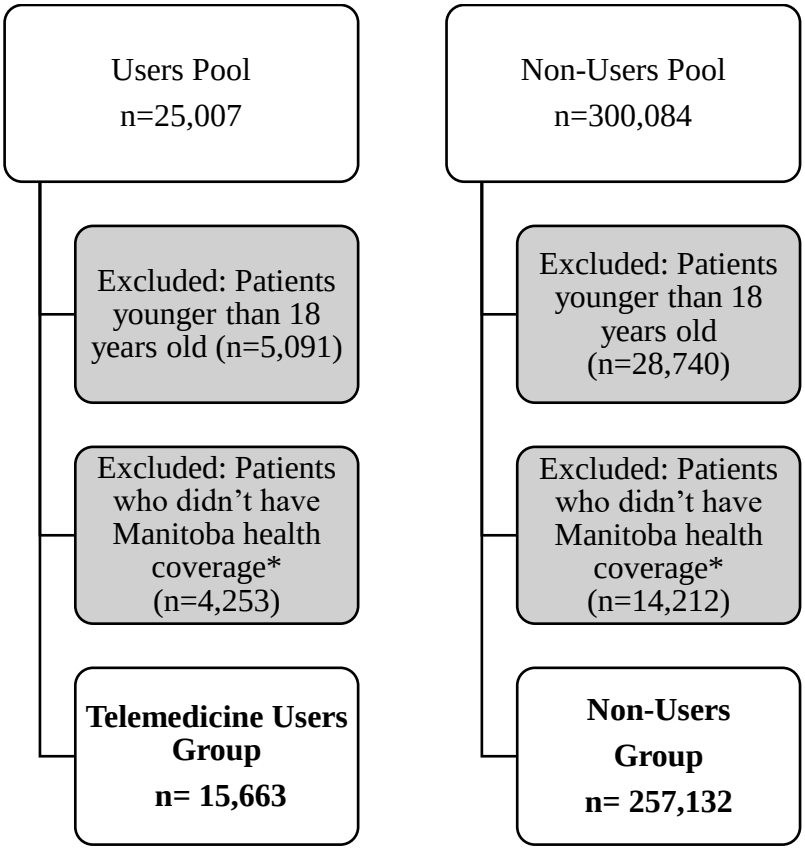
Data for this research was obtained by linking information from the Repository to records from the MBT program through scrambled personal health identification numbers. The Repository includes de-identified databases, so interactions with the system are tracked without identifying patients, covering health and social-service data for each Manitoba resident. (For validity and confidentiality of information housed at the Repository see Roos, Gupta, Soodeen, & Jebamani (2005), and Roos & Nicol (1999)). Specifically, this study links five databases: MBT Case Files, the Manitoba Health Insurance Registry, Medical Claims/Medical Services, Hospital Abstracts, and Pharmaceutical Claims.

Cohort Formation

To be included in the study sample, an individual needs to be part of the Manitoba Health Insurance Registry, have Manitoba health coverage throughout the study period, and be 18 years of age or older at the start of the study period. Figure 2 shows the study cohort development for both groups, telemedicine users and non-users. The group of telemedicine users contains all patients who used telemedicine at least once from December 2009 to December 2014, for a total of 25,007 patients. For non-users a sample of 300,084 patients who had never used telemedicine

was extracted from the Repository. This is 12 times bigger than the treatment group and well above the recommended acceptable ratio of 1:4 (Woodward, 2014). A larger sample was also not extracted for computational capacity limitations.

Figure 2. Cohort Development. Telemedicine Users and Non-Users



* for the two years before and after their index date

For telemedicine users the index date constitutes their first telemedicine consult. Because there is no clear index date for the patients in the control group, random index dates are assigned throughout the study period (December 2009 to December 2014). This allows for a more homogenous time frame for the measurement of outcomes (for 2 years after the index date) and

baseline characteristics compared with the treated individuals, who had their first telemedicine consult at various dates from December 2009 to December 2014.

Variables

Outcomes: Since most telemedicine consults in Manitoba are done with specialists (only 0.2% of consults in the sample are with primary care practitioners), this paper investigates first whether telemedicine has affected the number of in-person encounters with specialists. It is also analyzed whether telemedicine has any effect on the number of total in-person encounters (ambulatory visits), as well as the number of in-person visits to primary care physicians (PCP). Last, changes in hospitalization frequency are studied, since improved access could potentially increase diagnostic timeliness and adherence to treatment. Table 9 shows a detailed technical explanation of all outcomes. Each outcome is measured as a count to study the number of events.

Table 9. Technical Definitions of Outcomes Used

Indicator	Definition
Ambulatory face-to-face physician's visit, total	Almost all contacts with physicians, including office visits, walk-in clinics, home visits, and visits to outpatient departments. Exclusions include services provided to patients while admitted to hospitals, personal care homes (PCHs), emergency departments; and chiropractic claims. It also excludes services offered by primary care nurses.
Face-to-face visits to PCP	Including only visits to primary care practitioners (using general practice and family practice codes) from total ambulatory visits.

Face-to-face visits to Specialists	Excluding visits to primary care practitioners from total ambulatory visits.
Hospitalizations	Inpatient hospital episodes (i.e transfers within the same hospitalization are not counted as separate events) during which patients are formally admitted to the hospital for diagnostic, medical, or surgical treatment and typically stay for one or more days. Admissions to PCHs, nursing homes, nursing stations, and long–term care facilities are excluded.

Notes: Total ambulatory visits are a sum of visits to PCP and visits to Specialists. Definitions presented here are based on pre-existing work at MCHP using the same datasets.

Socio-demographic Covariates: For both, telemedicine users and non-users, we adjusted for sex, age, income quintile, regional health authority, distance to care and continuity of care. A set of health variables (dimensions) is also included, and these are explained in the statistical analysis section.

Distance to care is used as a general proxy for accessibility barriers to specialist care. In Manitoba, care provided by specialists (the main use of telemedicine) is concentrated in the Health Sciences Centre located in the capital, Winnipeg. The distance measure used here is defined as the number of kilometers from the patient's locale to the provincial center for specialists' services, measured 'as the crow flies' based on postal code.

Continuity of care, defined as the extent to which an individual sees a PCP over a specified period of time (Katz et al., 2014a), is also included as a confounder. The continuity of care index (COCI) weights the frequency of visits to each PCP and the dispersion of visits between physicians: $\mathrm{COCI} = \frac{(n_1^2+n_2^2+\ldots n_M^2)-N}{N(N-1)}$, where N is number of ambulatory visits, n_i is the number of visits to the ith physician, and M the number of potentially available physicians.

Measures range from 0 (each visit made to a different physician) to 1 (all visits made to the same physician). In this research, at least two ambulatory visits are needed in a two-year period for a patient to be included. (The inclusion of COCI as a covariate derives in the exclusion of low users, which will be later relaxed to test for sensitivity of the results.) Other measures of continuity of care commonly used in the literature include the usual provider index (UPC), to measure the density of visiting a physician frequently, and the sequential continuity (SECON) index, used to sequentially measure different physicians visited. This paper uses only COCI to measure continuity of care, based on findings by previous research (Smedby et al., 1986) which found that COCI is less sensitive to the number of physician visits (considering the high number of visits for some patients in the sample). Poor indicators of continuity of care at baseline could affect the level of healthcare services use, and specifically the rate of referrals to specialists through telemedicine.

Methods

Participation in the telemedicine program is not random, with physicians selecting patients based mainly on difficulties with access to care, and plausibly, clinical factors. A challenge with studying the effects of telemedicine is that participants in the telemedicine program may be systematically different from those patients who have never used telemedicine. To make these two groups of patients comparable we need to balance their baseline characteristics.

High-Dimensional Propensity Score:

To achieve this, a multi-step algorithm using high-dimensional propensity scores (hdPS) is first applied to predict the likelihood of using telemedicine for each outcome. The preference

for the hdPS method is based on findings by Guertin, Rahme, Dormuth, & LeLorier (2016) and Schneeweiss et al. (2009) regarding its superiority over any standard covariate adjustment chosen by an investigator. The algorithm used here to find the hdPS selects covariates from a database based on the variables' correlation to exposure and outcomes. Covariates are drawn from the two years before each patient's index date. The set of considered covariates includes: (1) medical service tariff codes; (2) physician diagnostic codes; (3) hospital procedures codes; (4) hospital diagnostic codes; and (5) prescription medication claims.

For each of these thousands of codes, the hdPS algorithm generates binary variables based on the frequency of occurrence for each code during the 2 years of pre-exposure. The algorithm then ranks each variable based on its potential for bias by assessing the variable's prevalence and association with the treatment and outcome. From this ranking, researchers determine the number of variables to include in the hdPS model (*n*). The purpose of these covariates is to control among other factors for comorbidity conditions, concurrent medication use, and disease severity. It should be understood as a set of proxies that indirectly describes the health status of the patient, and in general, collectively serves as proxies for unobserved confounders. Additionally, other sociodemographic variables are included (sex, age, income quintile, regional health authority, and distance to care). For each outcome, propensity scores are computed including all sociodemographic variables and the top 250 health covariates (results when choosing a higher number of covariates do not substantially change the estimations).

Since the algorithms used to create the hdPSs select variables based on correlation to both exposure and outcomes, the variables selected could differ for each of the four outcome models. Additionally, to ensure credible comparisons with better-balanced covariates, a common support

condition is imposed by trimming certain values of the propensity scores, as will be explained in the results section.

Inverse Probability of Treatment Weights:

To adjust for the confounders included in the hdPS, Inverse Probability of Treatment Weights (IPTWs) are used. The propensity score is the probability of a patient receiving a treatment (using telemedicine), conditional on a set of observed baseline covariates: e = P (Z = 1|X), where Z = 1 for patients being treated, Z = 0 for patients not being treated, and X denotes the vector of baseline covariates. The IPTW is then defined as $w = (Z/e) + (1 - Z)/(1 - e)$, for both the treatment and control groups. This way, the weight would be one divided by the propensity score for treated subjects, and one divided by one minus the propensity score for controls. Using these weights, among patients with the same value of the propensity score, individuals in the treated and control groups end up collectively counting the same. To assess balance in baseline characteristics between individuals in the treated and control groups, standardized mean differences are computed between the unweighted sample and the one weighted by IPTW, to determine whether a significant reduction is achieved.

Weighted Regression Model with Alternative Outcomes:

After obtaining the IPTW, a regression model can be estimated, and so obtain effects of telemedicine on utilization. The estimation strategy of combining regression models with IPTW is also called augmented-IPTW or doubly-robust estimation. The double-robustness property is particularly appealing because the estimator is consistent if either the propensity score model or the outcome regression model is correctly specified. (Wooldridge (2010) and Imbens & Rubin (2015) offer formal derivations and discussion of the double robustness result.)

The regression models incorporate the calculated weights, using generalized linear models. The dependent variables are all four different measures of use (total face-to-face visits, visits to PCP, visits to specialists, and hospitalizations). The set of independent variables includes a dummy variable ('case', with a value of 1 for telemedicine patients and zero otherwise), sex, age, income quintile, regional health authority, continuity of care, and distance to care. A zero-truncated negative binomial model is conducted, since it is appropriate for count data when overdispersion is present, and when zeros are not allowed in the data-generating process. (When counting face-to-face visits and hospitalizations patients who did not see a physician will be missing from the database). Asymptotic ('sandwich') variance estimators are used to account for the possibility of the pseudo-population being larger than the original sample size.

Results

General Case

During the period under analysis (December 2009 to December 2014), the telemedicine study group of 15,663 telemedicine users registered over 43,270 interactions with MBT. Table 10 presents descriptive statistics for the telemedicine study group. Patients using telemedicine are concentrated outside the main urban areas (as also shown in Figure 3) [7], which suggests use of the service for avoiding travel and time losses, and to increase access to populations who have

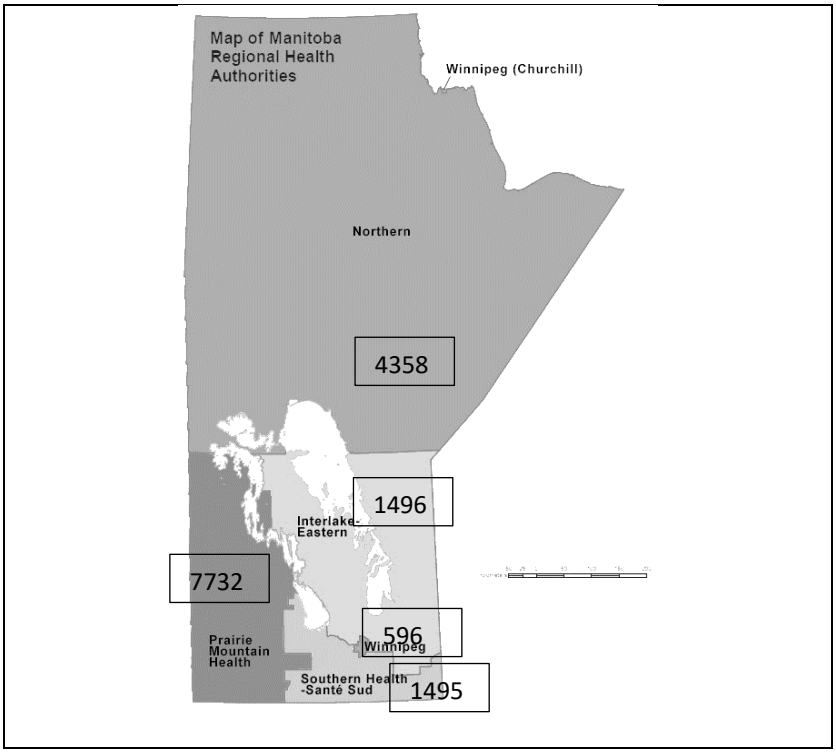
[7] Winnipeg residents are infrequent users of telemedicine. Their number as shown in table 10 might be mainly from Churchill (in the north of the province, as shown in Figure 3), which is part of the Winnipeg regional health authority. It might also involve a transient population, since some northern and rural residents with health problems might have relocated to Winnipeg. Estimation results are robust to the exclusion of this subset of patients.

otherwise not been able to receive medical attention. The primary specialities for telemedicine consultations are oncology (33% of consults), anesthesia (9%), psychiatry (8%), respirology (7%), general surgery (6%), and speech-language pathology (5%). The number of consults with primary care practitioners is low (around 0.2%). Since the principal aim of the MBT program is to improve access, telemedicine has been used to connect patients outside of Winnipeg with specialists, which are all located at the Health Sciences Center, in Winnipeg. That many telemedicine visits in Manitoba are with specialists also suggests that visits using telemedicine complement primary care.

Table 10. Descriptive Characteristics. Telemedicine Users and Non-Users

	Telemedicine Users		Non-Users	
	Mean	**SD**	**Mean**	**SD**
Age	54.10	17.64	62.67	15.27
Distance to Specialists' Services (km)	323.03	207.16	77.87	138.18
Continuity of Care Index	0.55	(0.30	0.67	0.32
	N	**%**	**N**	**%**
Sex				
Female	8,752	56%	139,575	54%
Male	6,911	44%	117,557	46%
Income Quintile				
Q1	4,633	30%	48,728	19%
Q2	3,615	23%	54,517	21%
Q3	3,347	22%	56,447	22%
Q4	2,513	16%	50,611	20%
Q5	1,392	9%	44,356	17%
Regional Health Authority				
Interlake-Eastern	1,406	9%	28,801	11%
Northern	4,358	28%	10,721	4%
Southern Health	1,495	9%	31,966	13%
Prairie Mountain	7,732	50%	34,876	14%
Winnipeg	5,96	4%	150,263	58%
	Mean	**SD**	**Mean**	**SD**
Outcomes				
Ambulatory Visits	18	14.11	12.16	10.16
Visits to Primary Care Practitioners	14.14	11.76	9.22	7.67
Visits to Specialists	5.53	6.15	4.97	6.03
Hospitalizations	2.2	2.03	1.76	1.36

Figure 3. Distribution across Regional Health Authorities Manitoba, Telemedicine users



As can be observed in table 10 there are differences between the group of telemedicine users and non-users. Furthermore, table 10 shows some descriptive statistics on the four utilization outcomes for the sample of patients, divided by telemedicine users and non-users. In all cases, users show a higher number of in-person encounters and hospitalizations, as an average.

The first step in the analysis is to obtain the propensity scores. The health variables included in the hdPS calculation differed for each outcome analysis, since they are selected based on correlation to the exposure variable (receiving telemedicine) and the outcome. Additionally, to ensure common support, the top and bottom 5% of the propensity scores are

trimmed. (Alternative estimations with other trimming values are also conducted and the results remain stable.)

The weighted sample is significantly better balanced in observables than the unweighted sample. Appendix B.1 shows how computed standardized differences improved for the weighted sample by outcome. Here, a covariate is considered to be balanced when the standardized difference is less than 0.25 (Harder et al., 2010). For some variables, standardized differences are significantly small in the unweighted sample, while remaining near the acceptable level after applying the weights. (Standardized differences for the remaining regressions are available from the author upon request.)

The next step is to estimate the weighted outcome models (zero-truncated negative binomial models). Transformed estimated coefficients for the variable 'case' are presented to find the effect of telemedicine on the outcomes of interest. Transforming the coefficients in terms of incidence-rate ratio, that is e^{β} rather than β, provides a more useful interpretations for policy recommendations.

Table 11 contains IPTW-adjusted coefficients for the variable 'case' for each outcome. Patients using telemedicine show a consistent increase in utilization. Specifically, participating in the telemedicine program is associated with total, primary care and specialists' face-to-face visits being 32%, 26%, and 38% higher, respectively. However, that is not the case for the variable hospitalization which is found to be 14% higher for telemedicine users than for non-users, even though the coefficient is not statistically significant.

Table 11. IPTW-Adjusted Effect of Telemedicine

	N	Incidence-rate	95 % CI
Ambulatory Visits	210,770 (N1=7,833)	1.32*** (0.04)	1.23 1.41
Visits to Primary Care Practitioners	208,752 (N1=7,721)	1.26*** (0.04)	1.17 1.35
Visits to Specialists	136,718 (N1=6,396)	1.38*** (0.11)	1.19 1.61
Hospitalizations	69,352 (N1=5,442)	1.14 (0.13)	0.91 1.43

Notes: Significance at α= 0.01, 0.05, and 0.1 is denoted by ***, **, and *, respectively. Standard error in parenthesis. N1 denotes telemedicine patients.

The inclusion in the estimations of the variable COCI (requiring at least 2 visits to a PCP in a 2-year period) derives in an exclusion of low users. Given the potential selection bias associated with this exclusion, a sensitivity analysis was conducted without the variable COCI in the regression, but reincluding low users. Results remain stable as shown in Appendix B.2.

Results are also robust to limiting the analysis to patients living further away from care. Table 12 shows estimations for three different cases of distance to care. First, only patients living 200 km and 300 km away from the centre for specialists' services are included. (Choosing a distance to care over 300 km is not considered, given the significant reduction in sample size.) Estimations for those patients living in the northern part of the province (as defined by the regional health authorities) are also included. Results shown in table 12 are similar to the ones in table 11, both in effect size and direction.

Table 12. IPTW-Adjusted Effect of Telemedicine. Patients living further away from care

	N	Incidence-rate	95 % CI
Patients living further than 200 km from Specialists' Care			
Ambulatory Visits	34,864 (N1=7,926)	1.29*** (0.02)	1.26 1.33
Visits to Primary Care Practitioners	34,508 (N1=7,804)	1.26*** (0.02)	1.22 1.29
Visits to Specialists	20,302 (N1=6,073)	1.26*** (0.03)	1.20 1.33
Hospitalizations	14,217 (N1=4,705)	0.99 (0.05)	0.92 1.09
Patients living further than 300 km from Specialists' Care			
Ambulatory Visits	16,389 (N1=5,362)	1.23*** (0.02)	1.19 1.28
Visits to Primary Care Practitioners	16,151 (N1=5,254)	1.22*** (0.03)	1.17 1.27
Visits to Specialists	9,504 (N1=3,949)	1.20*** (0.05)	1.11 1.29
Hospitalizations	6,854 (N1=3,222)	1.02 (0.06)	0.90 1.15
Patients living in the Northern Regional Health Authority			
Ambulatory Visits	10,548 (N1=3,101)	1.29*** (0.03)	1.23 1.35
Visits to Primary Care Practitioners	10,357 (N1=3,022)	1.24*** (0.03)	1.18 1.31
Visits to Specialists	6,551 (N1=2,446)	1.27*** (0.06)	1.16 1.39
Hospitalizations	4,140 (N1=1,610)	1.03 (0.07)	0.90 1.19

Notes: Significance at α= 0.01, 0.05, and 0.1 is denoted by ***, **, and *, respectively. Standard error in parenthesis. N1 denotes telemedicine patients.

Beyond the General Case

This section limits the previous general analysis, which included all (eligible) telemedicine patients, to two special cases. First, it is studied how results vary for specific conditions, namely diabetes and hypertension. Second, the paper investigates how results differ

for different relative levels of telemedicine use. For all estimations in this section, instead of trimming the top and bottom 5% of observations, the top 5% and all observations with propensity score values under 0.02 are trimmed, since this improved standardized differences between the unweighted and weighted sample. Even though this resulted in a smaller sample size, estimation results are robust to the change in trimming criteria.

Chronic Conditions:

The previous analysis shown in table 11 is replicated, but now the sample is restricted (including patients in the treatment and control groups) to those patients with either diabetes or hypertension. Much previous work in the literature has shown special interest on the effects of telemedicine for chronic patients, given the potential benefits that closer involvement of healthcare staff with patients might bring to disease management, as well as the potential reduction of costs for the healthcare system. From the initial sample of 15,663 telemedicine patients, 2,885 and 7,689 are patients living with diabetes and hypertension, respectively, and diagnosed within the five years before 2009. (See Appendix B.3 for the criteria used to measure prevalence.)

Results in table 13 have the same sign as in the general case: patients with chronic conditions show also greater numbers of face-to-face visits and number of hospitalizations. However, the magnitude of the telemedicine effect varies across conditions. For all ambulatory visit outcomes, patients with diabetes show higher percentage increases over their non-user counterparts in comparison with the hypertension case. For example, while receiving telemedicine is associated with total face-to-face visits being around 19% higher for patients with hypertension using telemedicine, for patients with diabetes outcomes are around 22%

higher. For both chronic conditions, hospitalizations are now statistically significant, showing increases of some 35% with respect to non-telemedicine users.

Table 13. IPTW-Adjusted Effect of Telemedicine. Patients with Chronic Conditions

	N	Incidence-rate	95 % CI
DIABETES			
Ambulatory Visits	17,935 (N1=1,394)	1.22*** (0.03)	1.17 1.27
Visits to Primary Care Practitioners	17,790 (N1=1,373)	1.16*** (0.03)	1.11 1.21
Visits to Specialists	13,631 (N1=1,222)	1.33*** (0.06)	1.22 1.45
Hospitalizations	9,235 (N1=1,129)	1.34*** (0.08)	1.20 1.49
HYPERTENSION			
Ambulatory Visits	48,665 (N1=3,041)	1.19*** (0.02)	1.15 1.23
Visits to Primary Care Practitioners	48,567 (N1=3,055)	1.14*** (0.02)	1.10 1.18
Visits to Specialists	34,404 (N1=2,573)	1.29*** (0.04)	1.22 1.37
Hospitalizations	25,355 (N1=2,559)	1.36*** (0.06)	1.25 1.48

Notes: Significance at α= 0.01, 0.05, and 0.1 is denoted by ***, **, and *, respectively. Standard error in parenthesis. For the outcomes ambulatory visits to specialists and hospitalization for the hypertension case, the hdPS model is constructed including only the top 125 health covariates – instead of the top 250. The reduction of covariates is chosen to assure the validity of the model fit. N1 denotes telemedicine patients.

Dosage Effect:

Effects of telemedicine might also differ depending on the degree of intensity the service is used, in relation to regular face-to-face visits. This paper defines intensity of telemedicine use as the proportion of total visits with specialists provided through telemedicine, multiplied by a concentration of care index (CCI). The analysis is limited to visits with specialists, since

telemedicine consults in Manitoba are conducted almost exclusively with specialists. The CCI is calculated as follows:

$$\text{CCI} = \frac{(n_1^2+n_2^2+\ldots n_M^2)-N}{N(N-1)} \quad (3)$$

where N is the number of visits to specialists through telemedicine, n_i is the number of visits to the ith specialist, and M the number of potentially available providers. This borrows the notion of a continuity of care index, with an important distinction being that COCI are calculated at a primary-care level (including only PCP visits).

The proposed intensity indicator reflects the proportion of visits done through telemedicine, and its distribution across different providers. (Note that these proportions are calculated for the two years after starting using telemedicine.) This way, two patients with the same proportion of telemedicine consults might score differently in terms of the intensity of telemedicine use (patients with smaller values of concentration scoring lower). Since patients in Manitoba might be using the telemedicine service for different specialties, the created intensity indicator serves also as a measure of spread across services used.

To assess the effect of telemedicine on those patients who use it more frequently and whose visits are more concentrated across specialties, the general analysis is replicated, limiting the sample to those patients whose intensity of telemedicine use index is first over 40%, and second over 50%. (Proportions greater than 50% are excluded, due to sample size constraints.)

Once the treatment group is limited to telemedicine high-intensity users, the effects differ from the general sample, with the most significant being changes in visits to specialists. As shown in table 14, patients using telemedicine are found to have lower rates of specialists' face-

to-face visits. The numbers of total and PCP visits are found to be higher for users, as for the general case, but magnitudes of the effect vary. Additionally, the hospitalization outcome is found to be not statistically significant. It is relevant that patients in this high-frequency category are distributed across all regional health authorities, and present similar socioeconomic characteristics as the general population of telemedicine users (see Appendix B.4).

Table 14. IPTW-Adjusted Effect of Telemedicine. Intensity Effect

	N	**Incidence-rate**	**95 % CI**
	Telemedicine consults over 40% of total visits		
Ambulatory Visits	23,456 (N1=1,021)	1.22*** (0.03)	1.16 1.28
Visits to Primary Care Practitioners	22,959 (N1=1.014)	1.32*** (0.03)	1.25 1.39
Visits to Specialists	21,167 (N1=1,292)	0.48*** (0.03)	0.44 0.54
Hospitalizations	12,363 (N1=799)	1.09 (0.10)	0.91 1.30
	Telemedicine consults over 50% of total visits		
Ambulatory Visits	18,965 (N1=750)	1.19*** (0.03)	1.12 1.26
Visits to Primary Care Practitioners	18,405 (N1=712)	1.29*** (0.04)	1.22 1.37
Visits to Specialists	18,397 (N1=1,019)	0.34*** (0.02)	0.30 0.38
Hospitalizations	10,600 (N1=599)	0.99 (0.08)	0.83 1.17

Notes: Significance at α= 0.01, 0.05, and 0.1 is denoted by ***, **, and *, respectively. Standard error in parenthesis. N1 denotes telemedicine patients.

Discussion

The telemedicine field has advanced its promise to improve access, costs and quality of care. However, how these programs relate to standard care is a question that remains unanswered. The existent literature is somewhat inconsistent, in that while most research

supports telemedicine in principle, it also recognizes inconclusiveness, ambiguous findings and a lack of rigorous research.

This paper contributes to the body of research by providing rigorous empirical evidence of the heterogeneous effects of telemedicine on utilization outcomes, including total in-person visits, PCP visits, and specialist visits, as well as hospitalizations. Estimations conducted show evidence of higher use of healthcare services for telemedicine users. The magnitude of this effect varies depending on whether the patient had a chronic condition (diabetes and hypertension), and how far the patient lived from medical attention. Consistent with our findings, Ashwood et al., (2017) found that patients using telemedicine showed increased contact with physicians, rather than substituted virtual with in-person visits. In a study of acute respiratory infections, the authors estimated that as much as 88% of telemedicine visits were new utilization rather than substitution, and that savings from substitutions were outweighed by the new utilization. One explanation for the observed increase in use is the existence of a previously unmet demand, which sheds light on the potential of telemedicine for closing gaps in access to medical attention. Evidence of significant expansion in service through telemedicine exists for traditionally access-constrained specialties and groups such as dermatology and mental healthcare for rural patients (Mehrotra et al., 2016; Uscher-Pines et al., 2016; Uscher-Pines & Mehrotra, 2014). In the case of Manitoba, the observed increase in use is consistent with improved access being the primary purpose of the MBT program.

Different results are obtained for the more limited sample of high-intensity users of telemedicine services. Most noticeable, while total in-person visits and PCP visits are still higher for telemedicine patients, telemedicine users have fewer specialist visits than non-users. Because

telemedicine, in the case of Manitoba, is mainly been used for specialist services, these results indicate that, when telemedicine is implemented continuously, and not as isolated encounters, users show a reduction in their in-person care compared to non-users. Under the premise that virtual visits reduced time in comparison with in-person visits (Ashwood et al., 2017; MBT, 2011), the remaining time of specialists could be used by patients in the waiting list, further improving access. Importantly, this research shows that using telemedicine at a higher intensity is not necessarily related to patients' health conditions or sociodemographic characteristics (see Appendix B.4). This suggests limiting telemedicine to specific subpopulations to serve as complement of regular care management and clinical decision support should not necessarily follow parameters such as distance to care restrictions, predominance of chronic conditions, income quintile, gender, or age. Clearly deeper investigation is needed.

A decline in utilization linked to higher levels of telemedicine intensity has been found for emergency visits and hospitalizations of patients in nursing homes (Grabowski & O'Malley, 2014; Shah et al., 2015), but there is not much evidence in ambulatory care settings. Shah et al. (2018) encountered a significant decrease in use of in-person ambulatory services for the first quarter-year after patient's registered with a telemedicine program, which occurred parallel to the peak in virtual visits. However, after the initial period, in-person visits started to grow and virtual visits to decline. Fluctuations in use over time, besides program design, also requires a closer look at satisfaction and perceived quality. Telemedicine acceptance by providers and patients has not always been easy. Some of the barriers identified by the existent literature are potential breakdowns in patient–physician relationships, privacy concerns (Anthony et al., 2018), and organizational difficulties. For the latter, reimbursement, billing insurers, and paying providers were identified as drawbacks in a US study of health centers' adoption by (Lin et al.,

2018). In Manitoba, where a previous study showed high satisfaction with the telemedicine program (MBT, 2011), as longer data series become available, potential explanations behind utilization patterns could be supported by closer look at over time fluctuations.

This research adds to the existent literature by exploiting a high-quality population-based dataset. The availability of information on each patient's interaction with the healthcare system, allowed to successfully balance health status and socio-demographic features between users and non-users. The results obtained were robust to various specifications. Further research might consider additional potential confounders such as: controlling for the changes in the different technologies used over the studied time period; the skill that physicians bring to using telemedicine technologies; and the effect of local service capacity, which varies depending on availability and expertise.

Enhancements in how to measure utilization should also be included in future telemedicine evaluations. Registering the total number of consults differentiating by in-person visits, phone-calls, electronic messages, video-conference, and other forms of information technology, as well as time spent for each interaction, might bring greater insights into a comprehensive evaluation of care provided and physician's time and effort. Likewise, beyond the various forms of virtual communication, improved documentation of the depth and breadth of transmission of data between physician and patient might bring a new perspective on virtual care. For example, information gathered in patient portals or through electronic transmission of data from medical devices can considerably improved decision making and clinical support, elevating quality of care.

Finally, though exploring how patients using telemedicine modify their in-person use of healthcare services is this article's main contribution, utilization is only one component in evaluating the economic value of telemedicine. A complete assessment of value needs additional work, including measuring benefits in health outcomes and quality of care improvements. In the longer run, for example, increased access and convenience can contribute to closer patient-physician relationships that improve continuity of care, which has been shown to reduce hospitalizations (Bayliss et al., 2015) and rates of complications (Hussey et al., 2014), as well as improving preventive care (Anhang Price et al., 2010). Showing value of telemedicine in an ambulatory care setting is crucial for better mapping the challenges associated with future transitioning of care delivered virtually.

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Chapter 3. The Impact of EMR facilitated Primary Care on Health Outcomes

Introduction

The use of digital records of patients in healthcare have been growing in Canada, with estimates pointing to only 15% of primary care physicians still using paper-based records by 2017 (Gheorghiu & Leaver, 2019). The terms used to describe the variety of these digital health records are based on three main criteria: completeness of information, custodian of information (healthcare providers or patients), and recently, the care setting of the solution (Canada Health Infoway, 2011, 2016). For example, while the term electronic health record (EHR) refers to a complete health record (holding all relevant health information) with the healthcare provider as custodian, electronic medical record (EMR) refers to partial records and it is often described as provider-centric or health organization-centric. Personal health records, on the other hand, are either complete or partial records under the custodianship of a person.

But the completeness dimension is gradually being blurred since systems are increasingly holding greater information and interoperability is growing, at the same time that an emerging "care setting" dimension has brought another set of terms and specifications. An additional distinction now between EHR and EMR is the support of multiple care settings by the first one and the focus on community physician practice of the latter one (Canada Health Infoway, 2016). Likewise, other terms specific to a care setting are appearing, including hospital information systems (for inpatient care) and ambulatory EMRs (for outpatient settings - clinics). Nevertheless, the direction of health systems towards higher quality care supported by integrated

digital platforms across settings, geographic locations and providers will most likely result in a future merger of existing terms.

Specifically, an EMR, the term used throughout this paper, constitutes a secure and integrated digital collection of a patient's encounters with their clinician (Canada Health Infoway, 2019). This includes but is not limited to information on patient demographics, progress notes, medications, vital signs, medical history, immunizations, laboratory data and radiology reports (WHO, 2012). The term EMR also comprises an embedded set of professional decision support tools such as guidelines, expert analysis, reminders, and secure communication with other clinicians (WHO, 2012).

The potential for EMRs to contribute to an improved decision-making process is based on various functionalities. First, by automating and streamlining the entry of information, EMRs could enhance the workflow of physicians and medical care personnel, increasing productivity and reducing potential medical errors. Besides generating a record of each patient's contact with the system, EMR's facilitate other care related activities including evidence-based decision support, quality management, outcomes reporting, billing, and public disease surveillance. These benefits could, in principle, be linked to improved primary care practice leading to superior health outcomes, as well as decreased costs through improved efficiency. However, the empirical literature shows that results are mixed.

A review of EMR evaluations shows that the effect of implementing this technology is inconclusive and often yields conflicting results in terms of quality of care, productivity, and cost reduction (Lau et al., 2010). Some studies have seen increased adherence to standards of care (Cebul et al., 2011), and increased coverage of preventive care services (Guiriguet et al., 2016).

Others have found no effect on adherence to guidelines (Crosson et al., 2007), efficiency in workflow parameters (Perry et al., 2014; Tall et al., 2015) or general productivity (Huerta et al., 2013). As for healthcare utilization, the use of an EMR has been shown to decrease laboratory, radiology tests, and billing errors (Wang et al., 2003), complication errors and medication related adverse events (Hydari et al., 2018), as well as to reduce physician's visits (Garrido et al., 2005). Other research encountered negative effects in terms of cost savings (Himmelstein et al., 2010), modest or non-significant association with hospital utilization measured by length of stay, readmission rates and inpatient costs (DesRoches et al., 2010), and mixed results in terms of ambulatory costs for Medicare beneficiaries (Adler-Milstein et al., 2013). Mixed conclusions could be the result of varying stages in EMR adoption at the time of evaluation, differences in EMR systems, medical specialties, geographic locations, among many other factors.

Another reason behind EMRs not necessarily performing as expected is the associated physician burnout (Green, 2016). This might be the result of software limitations requiring physicians to divert attention from patients to managing data input. Limited functionalities and difficulties in software implementation and management may lead to frustration and underutilization, with subsequent impacts on patient care and quality indicators. It might also be the case that physicians are unable or unwilling to take the time to become proficient in the new digital systems. Trudel et al. (2017) describes a "ceiling effect" of EMRs in the Canadian primary care setting associated with factors such as limited learning and organizational inertia. As a learning process takes place, in the longer run under-utilization might decrease, as a result of newly graduated physicians entering the market "EMR ready" as well as newly introduced software programs being more user friendly.

A broader empirical literature exists on the application of data obtained from EMRs for healthcare research (J. Lin et al., 2013). However, existing work on the direct impact of EMR adoption on healthcare delivery is more limited and appears to be undeveloped in some areas. Specifically, research about how implementation of the EMR is associated with improved primary care does not account for the selection bias intrinsic to EMR implementation, whether this leads to better care/outcomes, and whether this improved primary care persists over time in the management of chronic conditions.

This research assesses the association between EMR facilitated care and paper-based primary care practices with patient outcomes in the Canadian province of Manitoba. This was achieved by assessing whether physicians delivering EMR facilitated primary care adhered more closely with established clinical norms compared to physicians delivering primary care in paper-based practices. To that end, a set of preventive care, chronic disease management, and utilization indicators were analyzed.

By using an augmented difference- in-differences approach with fixed effects to study a large administrative dataset, this paper also discusses the mechanisms through which EMRs could fail to affect the desired outcomes. One possibility is that limited software functionalities or poor implementation derive in weak association between the use of EMR and improved care delivery. Another is that an adaptation period will take place before improvements can be observed. Yet again, physicians may implement EMR's poorly and unevenly. Most importantly, this paper point towards a future research agenda of studies of EMR to explore these nuances.

The EMR Program in Manitoba

In 2010 the government of Manitoba launched its electronic medical record program. The initiative was supported by a new funding program to make it easier for family doctors to modernize their practices using EMRs with promises of increased efficiency, improved quality and safety of care, and improved management and access of patient information. Specifically, the program was designed to "reimburse eligible community physicians for up to 70 per cent of the eligible costs of purchasing and using qualified EMR products, and operating costs for the first two years" (Province of Manitoba, 2010).

Shared Health is the entity responsible for supporting the adoption and effective use of EMRs in Manitoba, which is achieved by setting standards for provincial EMR certification and managing the certification of EMR products (Shared Health, 2019a). EMR certification is a non-competitive process which focuses on the EMR product to determine its suitability according to clinical and administrative requirements, and to ensure it can reliably and securely integrate with Manitoba's provincial services. However, it does not include assessment on the product's usability, the EMR applicant's financial viability or their ancillary services (such as prices and implementation).

By using one of the two types of Manitoba certified EMR product, clinics have some assurance about the EMR meeting core information and reporting requirements (Shared Health, 2019c). A Standard EMR certification includes assessment of Manitoba's baseline EMR requirements along with eChart Manitoba (provincial electronic health record). Once certified at this level, vendors may choose to enhance their product by selecting optional components and work to eventually achieve full Integrated EMR certification. Integrated EMR Certification

provides another set of features including quality indicator reminders as well as secure electronic delivery of lab and diagnostic imaging results (eHeatlh_hub). It also includes interoperability elements focusing on centralized patient component functionality, and future clinical information sharing opportunities enabling exchange of data between primary and episodic providers (Shared Health, 2019a). To maintain certification, EMR products will be required to certify against updated or new requirements as applicable to their level of certification. Even though the certification approach reduces the probability of de-certification, "if a product no longer meets assessment criteria, Manitoba will work with the vendor to correct the deficiency before de-certification is considered" (Shared Health, 2019a).

The decision on which EMR product to use relies ultimately on individual healthcare providers and purchasers have the responsibility to ensure an EMR product meets their individual needs. An early qualitative analysis of EMRs in Manitoba identified some common challenges, such as how the EMR was implemented, the supporting eHealth infrastructure, lack of awareness or availability in EMR functionality, and poor EMR data quality (Price et al., 2013).

Provincial use of EMR increased after a slow adoption between 2010 and 2013. The increase in use motivated several studies validating the information collected through the newly adopted digital systems. One study concluded that the validity of EMR data, when compared with administrative health data, for ascertaining a variety of chronic diseases was just fair to good (Lix et al., 2017). Another set of studies assessed data quality by associating whether information gathered through *problem lists* (a common feature of EMRs that allows clinicians to record and later recall relevant medical history) accurately reflected chronic diseases defined by

prescriptions and disease billing diagnosis (Singer et al., 2016, 2017). List completeness varies by primary care provider, patient load, and the clinic's funding and organization model. Lastly, a study by Katz, Bogdanovic, & Soodeen (2010) compared a series of quality indicators extracted from EMRs with administrative data for clinics participating in the Physician Integrated Network, a provincial primary care renewal initiative. It was found that the quality of EMR extracts were limited by their dependence on the appropriate fields being both available in the EMR and routinely used by physician. Other factors that compromised data quality in the provincial records included missing coding, alternative coding, and unexplained loss of data (Coleman et al., 2015).

This study deviates from existing literature interested in validating the quality of data collected via EMRs and asks whether the mere act of EMR adoption can be associated with improved quality of care. This manuscript investigates: (1) Does adoption of an EMR improve adherence to standards of primary care and management of chronic conditions? and (2) Does adoption of an EMR change utilization of healthcare services for ambulatory care sensitive conditions? To the extent of our knowledge, this is the first study to address these questions at a population-based level.

Data

Outcomes

Using patient-level data from 2009 to 2017, this study explores the effect of EMR adoption by a PCP on three sets of outcomes. The first group comprises four preventive care indicators: screening for breast cancer, colon cancer and cervical cancer, and influenza

vaccination. The second set studies the management of two chronic diseases: asthma (receiving a long-term prescription medication), and diabetes (visiting an ophthalmologist). All these indicators assess whether adopting EMR changes adherence to guidelines in a primary care setting. Lastly, one additional indicator explores the number of hospitalizations for four ambulatory care sensitive conditions (ACSC); namely chronic obstructive pulmonary disease (COPD), asthma, congestive heart failure, and diabetes. This ascertains whether, and to what extent, the use of an EMR affects the use of the healthcare system for the studied conditions. By definition, ACSC are conditions where improved ambulatory care leads to a decrease in hospitalizations.

Table 15 explains each of the selected outcomes in more detail. The definitions of these conditions in the administrative data found in the Manitoba Population Research Data Repository have been validated in previous studies (Katz et al., 2010, 2014b, 2016), and it also follows the Canadian Institutes for Health Information (CIHI) Primary Care definitions (CIHI, 2012). Specifically, for measuring the selected outcomes this study links six databases: the Manitoba Health Insurance Registry, Medical Claims/Medical Services, Hospital Abstracts, Pharmaceutical Claims, and Manitoba Cancer Registry. The connection across different areas of the healthcare system is possible through the use of linkable de-identified data stored in the Population Research Data Repository housed at MCHP. Interactions with the system covering health and social-services data for all residents of Manitoba are tracked without identifying patients. To be included in the study sample, an individual needed to be part of the Manitoba Health Insurance Registry, and have Manitoba health coverage throughout the study period. Table 15 displays specific eligibility criteria for each of the indicators.

Table 15. Primary Care Quality Indicators Definitions

Indicator of Primary Care	Definition
Preventive Care	
Breast Cancer Screening	Eligibility: Female patients aged 50-69 Outcome: At least one mammogram in the previous two years Exclusions: Women with a history of breast cancer
Influenza vaccination	Eligibility: Adults aged 65 or older Outcome: At least one influenza vaccination in a year
Colon Cancer Screening	Eligibility: Adults aged 50 to 74 Outcome: At least one fecal occult blood test (FOBT) in the previous two years Exclusions: Patients with a history of colorectal cancer and those who have a colonoscopy in the last 10 years
Cervical Cancer Screening	Eligibility: Female patients aged 21-69 Outcome: At least one Papanicolaou (Pap) test in the previous three years Exclusions: Women with a history of cervical cancer
Chronic Disease Management	
Asthma care[8]	Eligibility: Patients aged 20 and older with a diagnosis of asthma and a repeat prescription of relievers (acute treatment medications) by the start of the study period. Outcome: At least one prescription for a long-term control of asthma in a year Exclusions: COPD patients
Diabetes Care	Eligibility: Patients aged 20-79 with a diagnosis of diabetes by the start of the study period Outcomes: At least one visit to either an optometrist or ophthalmologist in a year
Health Services Use. Ambulatory Care Sensitive Conditions	

[8] There are two kinds of medications available to treat asthma: relievers (acute-treatment medications) and controllers (also called preventers) which reduce inflammation in the airways when taken regularly. Asthma treatment guidelines recommend that all patients requiring the use of acute-treatment medication more than twice weekly should also be treated with long-acting anti-inflammatory medications (controllers) for long-term control (Katz et al., 2016)

Hospitalizations	Eligibility: Patients aged 18 or older Outcomes: Number of hospitalizations for four conditions: COPD, asthma, congestive heart failure, and diabetes (only the most responsible diagnosis is used)

Note: Refer to Appendix C.1 for codes used for each indicator.

Physician and Patient Selection

The studied outcomes were measured for 39,801 patients in Manitoba receiving care from 345 primary care practitioners. The cohort development strategy started by selecting the eligible population of primary care physicians and assigning them a (non) EMR user classification for the period under study. To that end, all primary care physicians active in Manitoba from 2009 to 2017 were included. The choice of time-period was based on the fact that the EMR program in Manitoba was launched in 2010, which still allows for a pre-launch period to measure outcomes of first adopters. 2017 was the most recent available data when estimations were conducted, and years before 2009 were not included to maximize sample size while considering continuous enrolment.

In order to assign a (non) EMR classification, the following three indicators were measured for each physician in the initial pool across the study period. These were created using the Manitoba Primary Care Research Network (MaPCReN), the Physician Master file, and the Medical Services database housed at MCHP. MaPCReN is part of the Canadian Primary Care Sentinel Surveillance Network, which is a Canadian electronic medical record surveillance system collecting EMR records of participating primary care providers. The moment when each of these "episodes" occurred (first appearance on MaPCReN, first registered use of *nonemr* and *emr* tariffs) is also recorded so that a timeline of changes in EMR status could be identified.

All three indicators used to assign a (non) EMR classification are outlined below:

- A variable (*cpssn*) that flags whether the physician appears on MaPCReN. Not all EMR users participate in MaPCReN but all those in MaPCReN are users of EMRs. (Note that there might be a lag between the moment a participating physician starts appearing on MaPCReN records and the initial moment of EMR adoption. This issue will be further discussed below).
- A variable (*nonemr*) that flags whether the physician uses at least one of the tariff codes 8431, 8432, 8433, 8434, 8435, which are chronic disease management tariffs more likely claimed by family practitioners in paper-based practices.
- A variable (*emr*) that flags whether the physician uses at least one of the tariff codes 8454, 8455, 8456, 8457, 8458, which are comprehensive care management tariffs that require EMR enrolment. (Note that these *emr* tariffs started to be used in 2017 (Shared Health, 2019c). Extending the timeline until 2018 would have flagged more doctors as EMR users but it would have also left no follow up period for extracting outcomes.

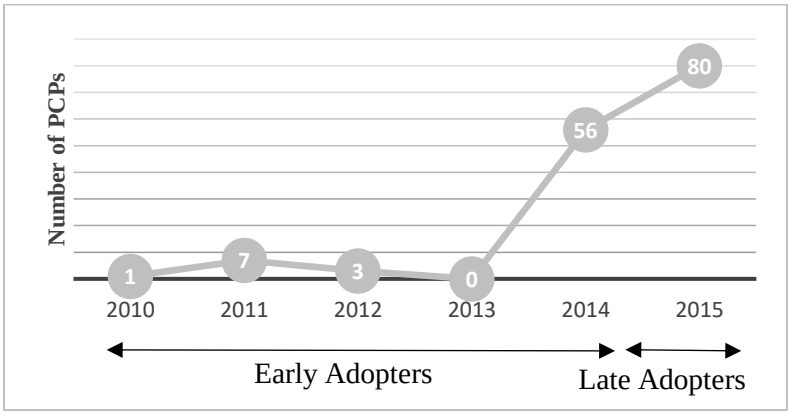
The initial sample was composed of 1761 providers. Since in the extracted records one provider can have more than one billing number, and consequently could have several values of *emr/nonemr/cpssn* associated, the data was cleaned as follows:

- Eliminating providers with a billing number but not a base number (base number is the unique identifier for each provider) (1 provider was eliminated).
- Eliminating those providers with different values for each of the indicators *emr/nonemr/cpcssn* across billing numbers, but keeping those with homogeneous criteria for each indicator across billing numbers (141 providers were eliminated)

By tabulating each physicians' classification for each of the three indicators a subset of EMR users and another one of never-users was created for a total of 1621 providers (Appendix C.2 shows a detailed tabulation). EMR users are those who appeared on MaPCReN. Non-EMR are those who never appeared on MaPCReN during the study period, have never used any of the codes associated with practices using EMRs, and who have used at least one the codes more likely associated with paper-based practices. The cross-reference of all three criteria adds confidence that the selected physicians under the non-EMR category actually work in paper-based practices during the study period.

The group of users contains a set of physicians who changed from paper-based practices to electronic heath records at some point during the study period (but mostly between 2014 and 2015). Graph 1 shows the different adoption dates for the selected group of users included in the estimations. For illustrative purposes, table 16 contains descriptive statistics that separate early adopters (before 2015) from late adopters (2015). The inclusion of users who adopted EMRs after 2015 was not possible because at least two years after EMR adoption are required to measure primary care outcomes.

Figure 4. Number of PCPs by year of EMR adoption



Note: These are only the PCP included in the estimations, after exclusion criteria were applied

The use of non-EMR users as a control group raises concerns about non-EMR users having potential inherent differences with the group of EMR users. These differences are noticeable in the lower panel of table 16. Never-users are older, predominantly male, and their patients show higher healthcare utilization. The identification strategy used in this paper overcomes this physician selection bias. It avoids the use of the more "obscure" group of non-users and instead exploits the variation in time of EMR adoption across the province for the different physicians in the users' group, as detailed in the methods section.

As for the sample of patients, for each of the selected physicians, medical records of each of their patients were selected for the study period, considering that the patient had provincial health coverage across all studied years. Those who received care from more than one physician that use/do not use EMR systems were initially allocated to the most responsible primary care practitioner, measured as the one with highest number of encounters, or highest net fee if same number of encounters. Those patients whose highest number of encounters were with physicians outside the selected sample were eliminated. Note that switching providers would not have

necessarily excluded a patient. Nevertheless, after applying the corresponding eligibility criteria for each outcome (see table 15), patients included in the estimations are only seeing the one primary care practitioner in the selected sample of physicians, which addresses concerns that the observed effect is related to changes in physician. Another important feature of the sample of patients is the stability of the panel used with continuous enrollment over time. This reduces the risk of selective entry and patient attrition acting as drivers of the results. Appendix C.3 shows the patient cohort development.

Table 16. Summary Statistics: Patient and Physician Attributes

(a) Patient Attributes	Users		Non-Users	
Number of patients	7,686		32,115	
Age	51.88		50.64	
Sex				
Male	24.04%		26.31%	
Female	75.96%		73.69%	
Urban	50.86%		72.01%	
Income Quintile	Urban	Rural	Urban	Rural
Q1	10.37%	10.63%	11.54%	4.54%
Q2	9.30%	9.85%	14.40%	5.64%
Q3	10.64%	6.96%	15.51%	6.97%
Q4	9.78%	11.42%	14.90%	5.09%
Q5	10.53%	10.06%	15.47%	5.60%
Preventive Care				
Breast Cancer Screening	0.72 (0.28)		0.75 (0.29)	
Influenza Vaccination	0.36 (0.26)		0.46 (0.27)	
Colon Cancer Screening	0.38 (0.24)		0.47 (0.29)	
Cervix Cancer Screening	0.69 (0.28)		0.71 (0.28)	
Chronic Disease Management				
Asthma Care	0.52 (0.33)		0.50 (0.34)	
Diabetes Care	0.54 (0.29)		0.51 (0.28)	
Utilization due to ACSC				
Hospitalizations	0.26 (0.34)		0.24 (0.27)	

(b) Physicians Attributes	Early Adopters	Late Adopters	Never Adopters
Number of physicians n=	67	80	198
Age (mean)	45.20	46.08	53.05
Payment Method			
Salaried	23.88%	52.50%	3.54%
Fee for service	76.12%	47.50%	96.46%
Sex			
Male	50.75%	33.75%	62.12%
Female	49.25%	66.25%	37.88%
Average Visits per Physician	3.33	3.29	3.85
Number of Patients Annual (at least one visit)	1,515.09	902.22	1,841.07
Average Billing (per patient visit)	$ 44.11	$ 40.95	$ 41.03

Note: Standard deviation in parenthesis. Preventive care and chronic disease management indicators are binary variables, and hospitalizations is measured as a count to study the number of events

Model

The effect of adopting an EMR on the selected set of outcomes was studied using a difference-in-differences approach. Difference-in-differences models compare changes in a specific indicator over time in a group affected by the policy change (EMR adoption) with a group not affected. Estimates from a difference-in-differences model are unbiased if the trend over time would have been the same between the treatment and comparison groups in the absence of the intervention (the results section presents more detail on testing the parallel trends assumption). When participation in the program of different groups of users varies across time, instead of a simple two period - two groups model, the standard difference-in-differences model is modified as outlined in equation 4 below. Details for this more complex type of model as well as previous uses in health interventions can be found in Wing, Simon, & Bello-Gomez (2018).

Specifically, the identification strategy exploits the fact that physicians made the transition from paper to electronic records at different points in time across the sample period. Outcomes can then be tracked before and after the switch at various moments in time and for different physicians. The model incorporates patient and year fixed effects because the same patients are followed over time as shown below:

$$Y_{jit} = \alpha_t + \mu_i + \varphi X_{jit} + \rho(\text{Post x EMR})_{it} + \theta(\text{During x EMR})_{it} + \varepsilon_{jit} \quad (4)$$

Where Y_{jit} represents all different outcome variables for patient *i* with physician *j* in year *t*. α_t is a year fixed effect term, and μ_i a patient fixed effect term. Contrary to previous work on healthcare evaluations (David et al., 2015, 2018) practice fixed effects are not applied since in the sample the patient remained seeing the same primary care practitioner. X_{jit} captures time-varying physician and patient characteristics, including whether the patient lives in urban or rural area, patient income quintile, physician payment method, physicians age as well as an interaction variable between physicians age and sex (it might be the case than younger women, for example, might be more diligent about meeting standards). Estimations are robust to the exclusion of the interaction term.

The key explanatory variables are $(\text{Post x EMR})_{it}$ and $(\text{During x EMR})_{it}$, capturing each patient's EMR status during a given year. $(\text{During x EMR})_{it}$ flags the year of EMR transition, taking a value of 1 for that year and zero otherwise. When there exists some lag between the recorded point of adoption and the effective date of adoption $(\text{During x EMR})_{it}$ can be seen as an indicator of an initial stage of EMR adoption. $(\text{Post x EMR})_{it}$ takes value of 1 for each subsequent year and zero otherwise. The importance of accounting for the transition period in the study design of health reforms has been documented by Joynt et al. (2013). For the case of

EMRs in Manitoba, practitioners have faced challenges around the moment of adoption, mainly associated with populating the systems with patients' records and changes in workflow (Shared Health, 2019b).

To estimate the model, two types of regressions are used which depends on the outcome. For those outcomes represented by a dichotomous variable (all preventive care and disease management indicators) a logit model is estimated. For hospitalizations a Poisson model is used. All specifications employ robust standard errors.

Results

This section presents estimates of the impact of EMR on quality of care indicators by estimating equation 4. Results are reported in table 17 as percentage changes or marginal effects in the form of semi-elasticities for logit regressions and incidence rate-rations for the case of Poisson regressions.

Results indicate that EMR adoption had no impact on the preventive care indicators under study, as all coefficients for cancer screening and influenza vaccination were not statistically significant. This is the case for both, the adoption period as well as subsequent years. The absence of EMR impact found here for prevention measures might not be surprising if the use of EMR functions and tools that facilitate tracking of such indicators and/or provide reminders are not available or regularly used in participating clinics. This highlights the importance of training and enforcement of standards of use in order to improve adherence to recommended guidelines. Likewise, EMR does not seem to affect utilization measured through hospitalizations due to ambulatory care sensitive conditions.

Table 17. Effect of EMRs on Quality of Care Indicators

Outcomes		N	Percentage Change	95% CI
Preventive Care (Logit)				
Breast Cancer Screening	Post x EMR	9,853	0.02 (0.05)	(-0.08 0.12)
	During x EMR		0.01 (0.03)	(-0.06 0.07)
Influenza Vaccination	Post x EMR	5,030	-0.15 (0.13)	(-0.41 0.10)
	During x EMR		0.01 (0.11)	(-0.20 0.22)
Colon Cancer Screening	Post x EMR	14,152	-0.05 (0.09)	(-0.23 0.13)
	During x EMR		0.06 (0.06)	(-0.06 0.18)
Cervix Cancer Screening	Post x EMR	33,009	0.004 (0.03)	(-0.06 0.07)
	During x EMR		-0.03 (0.02)	(-0.07 0.01)
Chronic Disease Management (Logit)				
Asthma Care	Post x EMR	3,740	-0.03 (0.13)	(-0.28 0.23)
	During x EMR		0.05 (0.10)	(-0.14 0.24)
Diabetes Care	Post x EMR	4,053	0.25** (0.12)	(0.02 0.49)
	During x EMR		0.18** (0.08)	(0.01 0.34)
Utilization due to ACSC (Poisson)				
Hospitalizations	Post x EMR	1,299	1.00 (0.43)	(0.43 2.32)
	During x EMR		0.99 (0.27)	(0.59 1.68)

Note: N refers to patient-year observations. Significance at α= 0.01, 0.05, and 0.1 is denoted by ***, **, and *, respectively. Robust standard error in parenthesis.

In the case of chronic disease management, treatment of asthma patients (as measured here) was also found not to be affected by EMRs. Patients with diabetes who were being attended in practices with EMRs showed, on average, a 25% higher probability of visiting an optometrist or ophthalmologist for the years after EMR adoption. The effect was around 18% during the transition year. This result seems in line with previous studies who have found that chronic disease patients benefit most from improved decision making through EMR systems

(Lessing & Hayman, 2018). The result also points to an increased number in referrals from the primary care practitioner to specialists and a consequent increase in utilization.

Note that there is an incremental effect of EMRs observed over time for the diabetes care indicator found to be statistically significant. The coefficient for the variable (During x EMR) is smaller than for (Post x EMR). This is indicative of differing impacts between an adoption period and subsequent years, and sheds lights on two relevant issues. First, it is important to incorporate both indicators in the analytical design and second, extending the study period when information becomes available might identify additional patterns in changes in quality of care. Specifically, there might be a learning curve over time, as newly qualified physicians enter the profession "EMR ready", recent adopters become more proficient, and patients come to expect/demand the enhanced information.

Patients included for estimations in table 17 are only those enrolled with physicians in practices which eventually transitioned to EMRs. However, there are another 32,115 patients who are enrolled with physicians that remained in paper-based practices during the study period. A sensitivity analysis was conducted by including this group of patients in the analysis. While there is no variation in the (Post x EMR) or the (During x EMR) variables for non-users, the variation in the dependent variables can still serve as counterfactual time trends for EMR users (David et al., 2018). Results from estimating equation 4 with non-users as a control group remain stable in significance and direction as shown in table 18.

Table 18. Effect of EMRs on Quality of Care Indicators. Alternative Control Group

Outcomes		Percentage Change	95% CI
Preventive Care (Logit)			
Breast Cancer Screening	Post x EMR	-0.02 (0.02)	(-0.06 0.02)
	During x EMR	-0.003 (0.02)	(-0.04 0.04)
Influenza Vaccination	Post x EMR	0.01 (0.06)	(-0.10 0.12)
	During x EMR	0.01 (0.07)	(-0.13 0.14)
Colon Cancer Screening	Post x EMR	-0.12 (0.04)	(-0.20 -0.05)
	During x EMR	-0.05 (0.04)	(-0.12 0.02)
Cervix Cancer Screening	Post x EMR	0.002 (0.02)	(-0.08 0.09)
	During x EMR	-0.01 (0.02)	(-0.07 0.02)
Chronic Disease Management (Logit)			
Asthma Care	Post x EMR	-0.01 (0.06)	(-0.13 0.10)
	During x EMR	0.05 (0.06)	(-0.08 0.17)
Diabetes Care	Post x EMR	0.05** (0.05)	(-0.05 0.15)
	During x EMR	0.03** (0.06)	(-0.08 0.14)
Utilization due to ACSC (Poisson)			
Hospitalizations	Post x EMR	1.24 (0.16)	(0.95 1.60)
	During x EMR	1.34* (0.23)	(0.96 1.87)

Note: N refers to patient-year observations. Significance at α= 0.01, 0.05, and 0.1 is denoted by ***, **, and *, respectively. Robust standard error in parenthesis.

Parallel Trend Tests

The reliability of results from a difference-in-differences analysis depends critically upon conforming the assumption of parallel trends, which requires that the treatment and control groups exhibit a similar trend in the absence of treatment. In this specific study, confirming parallel trends is essential since EMR adopters at each stage might differ in both, observable and unobservable characteristics. To test this assumption, we follow Cerulli & Ventura (2019) and

perform a test of the time leads significance using equation 4 which was first proposed by Autor (2003).

$$Y_{jit} = \alpha_t + \mu_i + \varphi X_{jit} + \beta_0 D_{it} + \beta_m \sum_{m=1}^{2} D_{it-m} + \beta_n \sum_{n=1}^{2} D_{it+n} + \varepsilon_{jit} \quad (5)$$

In this case, the specification captures time effects by including the adoption year (*t*), two leads (*m*) and two lags (*n*) of the treatment variable *D*. Testing whether the leads are jointly equal to zero is indirectly a test of the difference-in-differences assumption of parallel trends. The assumption holds if the leads in equation 5 are not jointly different from zero.

Among the studied set of outcomes, all indicators passed the test. Additionally, when obtaining a visual inspection of the time effect coefficient estimates versus the time-to-adopt indicators, the absence of a visible trend in the pre-period (that is, the coefficients are close to zero) confirms the parallel trend assumption. Plots for each outcome under study are showed in Appendix C.4. Coefficients in the adoption leads being close to zero indicate the difference-in-differences strategy is successful and that there is little to no evidence of an anticipatory response. This also helps to address questions regarding the potential lag between recorded and effective time of EMR adoption.

Discussion

This paper provides evidence that the adoption of EMRs does not automatically improve quality of care, nor does it necessarily reduce utilization of healthcare services. Among the set of indicators studied, preventive care, management of asthma, and the number of hospitalizations, showed no significant change due to EMR adoption. However, a significant increase in the

quality of diabetes care, as measured by visits to an ophthalmologist or optometrist, was found for EMR users.

Despite a disagreement in the existent evaluation literature regarding the impact of EMR adoption on utilization, decision-making, and more generally quality of care provided, this paper finds heterogenous results and suggests several potential underlying factors.

First, failure of EMRs to rise to its expectations in terms of, for example, improvements in preventive care, might be rooted in technology (mis)management or underutilization. Investments in health information technology, such as EMRs, can only be cost effective if health sector staff strives to achieve improvements in technology performance; and greater emphasis is placed on technology management rather than adoption (Bryan, Mitton, & Donaldson, 2014). Implementation focused strategies rather than expansion ones have proved to be more cost-effective in specific healthcare programs. (For example, Turner et al. (2011) found that the focus in the implementation of an English national chlamydia screening program should be on partner notification strategies, rather than expanding the male screening program). For the case of EMRs, performance issues are associated with mis-use or non-use of a wider set of EMR functions and add-ons such as clinical decision support systems or provision of educational materials, as well as poor data entry (Hamade et al., 2019). For example, the 2018 Canadian Physician Survey found that, among primary care physicians in EMR practices, 63% regularly use fewer than 5 functions while the remaining 37% uses six to nine functions of EMRs to support patient care (Canada Health Infoway, 2018).

Close to the management issue, it is also a functionality one. Higher functionality is associated with a wider set of functions and processes available through the digital platform, and

is also linked to higher stages of maturity as defined in frameworks such as the EMR Adoption and Maturity Model from Canada's Health Informatics Association (COACH, 2013; Trudel et al., 2017). If (some) existent EMR systems currently in used by healthcare professionals are scored low in terms of functionality/maturity, misalignment between goals and results are essentially guaranteed from the start, no matter how well EMRs are being managed. Some healthcare professionals in Canada think that a single software system should be established as the official platform for electronic records, after consultations including health professionals and patients (Goldman, 2019), which will guarantee a level of quality associated with greater functionality. When health technologies are being assessed, regulatory agencies have been largely mandated to focus on adoption, compromising the necessary balance with functional activities; and rates of decommissioning (disinvestment) of ineffective services is rather slow (Bryan et al., 2014).

For EMRs to maximize their effect on healthcare delivery an additional essential feature is the availability of information at all points of care and sites. Timely access to data for multiple authorized users, not necessarily geographically bound, is one the main advantages of investments in this type of information technology. The lack of compatibility between digital records from different suppliers, and their inability to connect with labs, X-ray clinics, and hospital records compromises the access of digital patients records at critical points of care such as emergency rooms (Goldman, 2019). This results in treatment being provided based on incomplete information, which risks incorrect diagnosis and avoidable side effects from drugs and treatments. In Manitoba, while Integrated EMRs offer some interoperability features, these are limited for Standard certified products.

Another relevant factor in the success of EMRs relates to the acceptance by EMR users, closely related to management and functionalities. The complexity of EMRs makes it imperative to have a good application design, training and implementation not to compromise acceptability of the new systems. Engagement of healthcare professionals with EMRs has been shown to be affected by vendor support and training (Edsall & Adler, 2011), quality of data content and information (Chang et al., 2012), as well as concerns about accessibility, reliability and utility (O'Donnell et al., 2018). As for patients, concerns have been raised around EMRs deriving in a eroded physician-patient interaction (mostly from physicians starring at a screen rather that their patient) but consensus have not been found in the literature (Alkureishi et al., 2016). Nevertheless, the known linked between level of patient satisfaction with their doctor on one side and quality of care on the other (Panagioti et al., 2018) calls for a careful treatment of EMR's effect on physician-patient communication.

In the case of Manitoba, several challenges and advantages have surrounded users acceptability of EMRs (a complete list of experiences by Manitoba Peer Supporters can be found by visiting Shared Health (2019b)). Among primary care physicians, the most common challenge was associated with the up-front time and mental energy to populate EMRs with patients' history, as well as the necessary changes to be made to established workflows. The most relevant advantages were organization and improved legibility, remote and quick access to patients' records, efficiency gains from the use of macros and templates, the ability to receive and manage labs electronically, as well as the research and aggregate data capabilities. Nurses and clinical assistants raised their own set of challenges associated mainly with the correct entry of information, including finding different features and selecting information such as diagnosis codes. They find particularly useful scheduler templates and referrals, search features, access to

appointment history, and customizable action buttons. Lastly, clinic managers highlighted the additional effort needed in standardizing and implementing process for consistency while also allowing flexibility to suit individual providers; but praised the improved security in records and continuity of care. Overall, the importance of investing in training, maintaining constant feedback between other EMR users and within clinic workers, carefully choosing a product that fits the practice, and learning proper reporting were identified as essential factors in EMR success.

Lastly, one additional reason behind the weak effect of EMR adoption found here is related to the selection of studied PCPs. Adoption of EMRs is a voluntary process. Consequently, a physician's decision to upgrade to electronic records might be associated with a parallel change in practices, hence obscuring the effect of EMR adoption itself. Additionally, inherent differences between patients treated by PCP adopters and non-adopters, not controlled for here, could also be driving the lack of observed effects for screening outcomes. If EMR adopters are those treating least adherent patients, there might not be much the PCP can do to change their behaviour of not seeking preventive care, despite the physician's recommendation.

Future studies of EMRs' effects on healthcare delivery and outcomes can greatly benefit from improvements in terms of quality of information on Manitoba's EMR adoption. Throughout the study period, the state of the EMR environment has changed, the number of approved providers of EMR software has declined, and technical capabilities/standards of the systems have increased. Information on the exact time (to the month) of implementation, type of EMR (standard versus integrated), and available add-ins supporting decision making can improve future evaluations. Likewise, understanding the determinants of the different timing in

EMR adoption, though outside the scope of this study, could add to the discussion regarding some of the challenges associated with EMR transition. It is also possible that a longer adaptation period takes place and additional years of data are needed before a significant impact can be observed. The 2018 Canadian Physician Survey states that physicians tend to establish their EMR use behaviour within the first two years of adopting EMR (Canada Health Infoway, 2018). In that sense, future studies could benefit from quantifying adoption of EMRs not as a binary phenomenon but one for which learning and skills of users are also captured. Adoption of EMRs and effective use of their added value, beyond that of a paper chart, lies in the hands of the physician operating it. This is a process that evolves over time and differs across physicians. The impact on quality of care could be more rigorously explored by accounting for these fluctuations.

Given the relatively early implementation of EMRs at the time the outcomes were measured, this study sheds lights on the impact of EMR adoption in clinical practice and health outcomes at an initial stage. Specifically, our findings provide evidence that investments in EMR adoption are not a guarantee of immediate benefits in terms of quality of care improvements and efficient care. Policy makers, health technology analysts, and other interested stakeholders should pay equal attention to management, functionality, and acceptability of the newly introduced EMRs, so that potentialities can be fully realized for EMRs to become more than merely electronic paper records.

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Conclusions

This thesis consists of three chapters which developed there independent, yet interconnected, research questions around technology and healthcare. The first chapter studied at an aggregate level to what extent medical technology drives healthcare expenditure. The second and third chapters explored the effect of two programs in Manitoba: telemedicine and electronic medical records on a set of healthcare and health outcomes.

In the first chapter results show that healthcare expenditure and medical technology are tied together by a long-run relationship for both panels of OECD countries and Canadian provinces. In order to avoid a growth in healthcare spending that could compromise long-term sustainability, policy makers should closely monitor and direct expenditure on new medical technology, as measured here. Results from the estimated ECM also differ significantly from previous estimations, which also show the importance of using out proposed dynamic approach which addresses the issues of cross-sectional dependence and parameter heterogeneity when modelling the relation between healthcare expenditures and technology. Lastly, our newly introduced proxies for medical technology constitute a relevant addition to the existent literature given not only their desirable time series properties, but also their conceptual superiority.

The second and third chapters found that evidence is not straightforward regarding the effects of telemedicine and EMRs in terms of use of healthcare services and outcomes. Telemedicine, on one hand, only under specific conditions effectively substitutes for regular care. EMRs, on the other hand, were found to show mixed results for the set of preventive care, chronic disease management and healthcare use indicators. Findings for both chapters are

consistent across different specifications of the propensity-weighted regressions and difference in difference models respectively, designed to control for selection on observables.

Appendix A. Supplemental Material for Chapter 1

Appendix A.1. Selective Review of the Literature: Medical Technology and Healthcare Expenditure.

Table A1. Selective Review of the Literature: Medical Technology and Healthcare Expenditure

Study	Time Span & Region	Variables	Technology proxies	Econometric Methods
Newhouse (1992)	US 1987	The spread of insurance, per capita income, aging, physicians, and productivity gains.	Residual component	Cross-section regression
Roberts (1999)	20 OECD countries 1960-1993	Per capita income, percentage of publicly funded healthcare spending, percentage of population aged over 65 years, relative price of healthcare, technological change	Time trend	Panel unit root and cointegration analysis (mean group ECM); Cross section; Pooled
Okunade and Murthy (2002)	US 1960-1997	Per capita disposable income, technological change	Economic-wide R&D and health sector R&D spending	Unit root and cointegration analysis (Johansen)
Koenig et al. (2003) * Hearle et al., (2003) conducts a similar analysis but focusing on outpatient services instead of physician services	US 1990-2000	Price inflation, demographics, physician supply, provider structure, technology and treatment patterns, health status, healthcare regulation, operating costs, health insurance, product design, etc.	Percent of total surgeries performed on an outpatient basis; Percent of hospitals with CT scanner, MRI, PET scanner, SPECT scanner, diagnostic radioisotope services; Percent of hospitals offering burn care and cardiac catheterization; Percent of	Panel regression analysis (state fixed-effect); Step-wise, pooled cross section, and OLS regressions

			hospitals with organ transplant capabilities; Number of academic health centers	
Di Matteo (2005)	US and Canada 1980-1998	Income, Age distribution	Time indicator variables	OLS regressions
Dreger and Reimers (2005)	21 OECD countries 1975-2001	Income and medical progress	Life expectancy, infant mortality and the share of the elderly	Panel unit root and cointegration tests by Pedroni (1999)
Bilgel and Trand (2013)	Canada 1975-2002	Income, relative price of health, share of publicly funded health expenditure, share of senior population, life expectancy at birth	Time Trend	Panel models (GMM, GIV)
De Mello-Sampayo and de Sousa-Vale (2014)	30 OECD countries 1990-2009	Income, Population Age, technology	Infant mortality	Panel unit root and cointegration analysis (MG-CCE)
Willemé and Dumont (2016)	18 OECD countries 1981-2012	Income, share of public/out-of pocket relative to total health care spending, age composition and average BMI	Medical devices and drugs approved by the FDA	Panel unit root analysis; Fixed effects estimator
Rossen and Faroque (2016)	Canada 1981-2011	Income, population aging, recession indicator, unemployment rate	Residual approach	OLS and IV
Murthy and Okunade (2016)	US 1960–2012	Income, population percent above 65 years and level of healthcare technology	R&D Expenditures	Unit root and cointegration analysis
Hauck and Zhang, (2016)	34 OECD countries 1980-2012	43 potential candidates including income, growth insurance premiums, financing arrangements, population aging, among others	R&D expenditures	CCE estimator and Bayesian inference

Murthy and Ketency (2017)	US 1960–2012	Income, life expectancy and technology	Real health R&D expenditure; Total R&D expenditure; Per capita real health R&D expenditure; Per capita real total R&D expenditure	Unit root and Cointegration tests that allow for multiple structural breaks
You and Okunade (2017)	Australia 1971-2011	Income and Technology	Proxies: Per capita R&D expenditure; Per capita hospital research expenditure; Hospital treatment coverage; Infant mortality rate; Proportion of population aged 65 and above; Unweighted and weighted medical device technology index. Residual Component	Unit root and cointegration analysis (Johansen)

Appendix A.2. Error Correction Model by unit of analysis.

Table A2. Error Correction Model by unit of analysis.

Panel A. OECD panel

	EC	ln(GDP)	ln(NMD)	ln(PMA)	ln(CTR)
Australia	-0.63178	-0.11443			-0.08813
	(0.008)	(0.714)			(0.008)
	-0.41562	-0.22885	0.153409	-0.0695	
	(0.06)	(0.675)	(0.058)	(0.717)	
Austria	-0.22423	2.551587			0.250351
	(0.134)	(0.48)			(0.142)
	-0.52031	0.487118	0.423776	0.565762	
	(0.009)	(0.787)	(0.237)	(0.119)	
Canada	-0.45182	0.452953			-0.08798
	(0.005)	(0.113)			(0.014)
	-0.72722	-0.40751	-0.24646	0.210827	
	(0.00)	(0.2)	(0.01)	(0.159)	
Denmark	-0.57888	0.5549			-0.09865
	(0.001)	(0.489)			(0.07)
	-1.18269	0.627127	-0.18104	-0.15933	
	(0.00)	(0.063)	(0.005)	(0.072)	
Finland	-0.50005	1.554958			0.047054
	(0.00)	(0.00)			(0.378)
	-0.57923	1.069432	-0.24322	0.524331	
	(0.00)	(0.002)	(0.098)	(0.033)	
Germany	-0.64853	-0.23229			-0.0041
	(0.004)	(0.501)			(0.909)
	-0.39634	-0.32667	0.225765	-0.6803	
	(0.079)	(0.65)	(0.098)	(0.012)	
Iceland	-0.43128	0.439968			-0.16439
	(0.062)	(0.451)			(0.106)
	-0.5215	1.373426	0.26592	0.749076	
	(0.04)	(0.211)	(0.548)	(0.21)	
Ireland	-0.35036	0.34425			-0.21055
	(0.01)	(0.554)			(0.309)
	-0.31489	0.751993	0.280827	-1.00664	
	(0.028)	(0.087)	(0.247)	(0.122)	
Japan	-0.62979	-0.46454			0.079146
	(0.001)	(0.041)			(0.11)
	-0.68436	-0.22781	0.076576	0.307771	

	(0.008)	(0.475)	(0.444)	(0.28)	
Korea	-0.60367	-0.31491			0.190876
	(0.002)	(0.34)			(0.071)
	-0.79672	0.466173	-0.31762	-0.12057	
	(0.00)	(0.13)	(0.019)	(0.706)	
Netherlands	-0.77803	-0.31633			0.007545
	(0.00)	(0.284)			(0.737)
	-0.87914	0.471736	-0.18156	0.281558	
	(0.00)	(0.184)	(0.001)	(0.019)	
New Zealand	-0.89434	0.404375			0.149912
	(0.00)	(0.048)			(0.00)
	-0.80274	-0.19554	-0.08223	-0.26259	
	(0.001)	(0.633)	(0.486)	(0.326)	
Norway	-0.94509	0.684022			-0.06688
	(0.00)	(0.086)			(0.072)
	-0.72066	0.263091	0.108603	-0.11055	
	(0.003)	(0.707)	(0.557)	(0.656)	
Portugal	-0.29073	1.966955			-0.36429
	(0.096)	(0.116)			(0.081)
	-0.57358	0.108234	0.696966	-0.09944	
	(0.0020	(0.902)	(0.031)	(0.839)	
Spain	-0.62811	1.603562			0.209378
	(0.00)	(0.051)			(0.00)
	-0.45359	1.820368	-0.05953	-0.15679	
	(0.022)	(0.188)	(0.753)	(0.663)	
Sweden	-0.69098	0.881057			0.000719
	(0.00)	(0.012)			(0.988)
	-0.74091	2.429772	0.421008	0.265133	
	(0.00)	(0.001)	(0.023)	(0.23)	
Turkey	-0.94933	0.539575			-0.02978
	(0.00)	(0.018)			(0.588)
	-0.64827	1.478905	0.482309	-0.62179	
	(0.024)	(0.017)	(0.046)	(0.448)	
United Kingdom	-0.51575	0.984958			-0.05428
	(0.008)	(0.506)			(0.46)
	-0.56343	1.384325	0.063603	-0.09706	
	(0.006)	(0.272)	(0.617)	(0.767)	
United States	-0.14418	2.013152			-0.04604
	(0.101)	(0.476)			0.641
	-0.1855	0.007917	-0.10209	0.251118	
	(0.112)	(0.997)	(0.525)	(0.645)	

Panel B. Canadian Panel

	EC	ln(GDP)	ln(NMD)	ln(PMA)	ln(CTR)
Alberta	-0.57468	0.486677			-0.13426
	(0.009)	(0.286)			(0.008)
	-0.40365	1.569784	-0.87272	-0.16154	
	(0.098)	(0.158)	(0.068)	(0.542)	
British Columbia	-0.40491	0.815612			-0.00479
	(0.027)	(0.025)			(0.921)
	-0.34606	1.221757	0.2659	-0.02563	
	(0.221)	(0.069)	(0.511)	(0.949)	
Manitoba	-0.78353	-0.1383			0.030947
	(0.00)	(0.763)			0.118
	-0.97981	-0.68394	0.224974	-0.10525	
	(0.00)	(0.034)	(0.008)	(0.11)	
New Brunswick	-0.86946	0.240267			0.013673
	(0.00)	(0.272)			(0.375)
	-0.89038	0.361848	-0.02176	-0.02806	
	(0.00)	(0.115)	(0.775)	(0.706)	
Newfoundland and Labrador	-0.86824	0.001788			0.036804
	(0.00)	(0.994)			(0.079)
	-0.74446	0.035616	0.228804	-0.11788	
	(0.00)	(0.862)	(0.055)	(0.275)	
Nova Scotia	-0.41579	-1.09883			-0.05007
	(0.003)	(0.311)			(0.441)
	-0.34913	-0.10216	0.094288	-0.33351	
	(0.045)	(0.951)	(0.852)	(0.553)	
Ontario	-0.69261	-0.02261			-0.01734
	(0.01)	(0.943)			(0.469)
	-0.84458	-0.55196	-0.28771	0.175106	
	(0.00)	(0.023)	(0.00)	(0.009)	
Prince Edward Island	-0.59631	0.493886			0.072918
	(0.008)	(0.618)			(0.242)
	-0.60752	0.340172	0.315119	-0.07458	
	(0.009)	(0.78)	(0.359)	(0.85)	
Quebec	-0.89351	-0.00109			-0.00017
	(0.00)	(0.997)			(0.991)
	-0.78909	-0.14943	-0.07741	0.021874	
	(0.001)	(0.66)	(0.324)	(0.788)	
Saskatchewan	-1.23827	0.340987			-0.05202

	(0.00)	(0.009)			(0.001)
	-0.93262	0.351006	-0.17203	0.038204	
	(0.00)	(0.093)	(0.138)	(0.624)	

Note: p value in parenthesis. Estimations are presented here only for model 1 (including GDP and technology proxies). Results for model 2 – adding proportion of the population over 65 years of age- are also similar in magnitude and statistical significance to the ones here and are available upon request.

Appendix A.3. Error Correction Model using Fixed Effects

Table A3. Error correction model estimated using an incorrect application of the fixed-effects model.

	Canadian sample		**OECD sample**	
	I	II	III	IV
EC	-0.137 [0.024]***	-0.076 [0.028]**	-0.114 [0.017]***	-0.098 [0.013]***
ln(GDP)	1.306 [0.2732]***	1.5336 [0.3622]***	1.268 [0.1407]***	1.2202 [0.115]***
ln(POP65)	-0.2984 [0.1491]**	-0.2983 [0.2191]	0.0899 [0.177]	0.1109 [0.1473]
ln(CTR)	0.0211 [0.0087]*		0.0233 [0.0121]*	
ln(NMD)		-0.1126 [0.0996]		-0.0976 [0.0731]
ln(PMA)		0.4744 [0.264]***		0.4797 [0.2571]*
RMSE	0.0258	0.0252	0.0377	0.0376
CD test	11.6112 (0.000)	8.593 (0.000)	3.5778 (0.000)	2.3465 (0.019)
Obs	320	350	608	665

Notes: The dependent variable for all models is the first difference of total healthcare expenditure expressed as logarithms, as are all independent variables. We present only the long-run coefficients. Estimations for the complete ECM are available on request. The depreciation rate considered for all technology variables is 10%.
RMSE is the root mean square error and CD test reports the Pesaran (2004) test with a null of cross-section independence with p values in parentheses. Significance at α = 0.01, 0.05, and 0.1 is denoted by ***, **, and *, respectively.
Three reasons this is an 'incorrect application' are detailed within the Methodology Section.

Appendix B. Supplemental Material for Chapter 2

Appendix B.1: Comparison of Baseline Characteristics. General Case. All Outcomes.

Notes: This table presents standardized differences for the sociodemographic variables and the top 10 health variables (as selected by the hdPS). Standardized differences for all health variables are available upon request.

Table B1. Comparison of Baseline Characteristics. Total Ambulatory Visits Outcome.

	Unweighted Standardized Differences	**IPT-Weighted Standardized Differences**
Characteristics at baseline		
Age	0.30	0.16
Distance to Care	1.21	0.10
Sex	0.01	0.07
Income Quintile Q1	0.17	0.17
Income Quintile Q2	0.06	0.05
Income Quintile Q3	0.003	0.08
Income Quintile Q4	0.07	0.08
Income Quintile Q5	0.21	0.03
RHA- IE	0.01	0.07
RHA- NO	0.57	0.08
RHA-SO	0.003	0.03
RHA-WE	0.75	0.008
RHA-WP	1.30	0.02
Health Status in the two years before index date		
Consultation	0.33	0.13
Office Visits Regional Intermediate Visit or Subsequent Visit or Well Baby Care	0.30	0.23
Electrocardiogram, Interpretation and Report by Physician who did not take tracing 12 LDS	0.34	0.21
Biochemistry, Creatine	0.65	0.06
Hospital care – Per day	0.31	0.19
Radiology Computerized axial tomography abdomen and/or pelvis exam	0.22	0.12
After Hours Premium – Weekend Days	0.33	0.13

Hematology, Counts, Blood, White Cell Count	0.51	0.03
Biochemistry, Glucose, Quantitative	0.69	0.12
Hematology, Hemoglobin (Photoelectric)	0.59	0.01

Table B2. Comparison of Baseline Characteristics. Ambulatory Visits to Primary Care Physicians Outcome.

	Unweighted Standardized Differences	**IPT-Weighted Standardized Differences**
Characteristics at baseline		
Age	0.30	0.14
Distance to Care	1.21	0.08
Sex	0.002	0.07
Income Quintile Q1	0.17	0.17
Income Quintile Q2	0.06	0.05
Income Quintile Q3	0.00	0.08
Income Quintile Q4	0.07	0.08
Income Quintile Q5	0.21	0.03
RHA- IE	0.01	0.08
RHA- NO	0.56	0.08
RHA-SO	0.001	0.04
RHA-WE	0.76	0.00
RHA-WP	1.30	0.04
Health Status in the two years before index date		
Office Visits Regional Intermediate Visits or Subsequent Visit or Well Baby Care	0.30	0.24
Consultation	0.33	0.13
Electrocardiogram, Interpretation and Report by Physician who did not take tracing 12 LDS	0.34	0.23
After Hours Premium – Weekend Days	0.33	0.13
Hospital care – Per day	0.31	0.21
After Hours Premiums -5:00 pm to 12:00 am	0.29	0.14
Special call to Emergency Room or OPD of a hospital	0.35	0.13
Radiology Computerized axial tomography abdomen and/or pelvis exam	0.22	0.14
V72 Special Investigations Examination	0.26	0.15

Immunizations – Influenza Vaccine – 1st dose (initial series)	0.34	0.01

Table B3. Comparison of Baseline Characteristics. Visits to Specialists Outcome.

	Unweighted Standardized Differences	**IPT-Weighted Standardized Differences**
Characteristics at baseline		
Age	0.33	0.25
Distance to Care	1.24	0.07
Sex	0.01	0.09
Income Quintile Q1	0.16	0.16
Income Quintile Q2	0.07	0.07
Income Quintile Q3	0.01	0.08
Income Quintile Q4	0.07	0.01
Income Quintile Q5	0.20	0.002
RHA- IE	0.05	0.07
RHA- NO	0.58	0.07
RHA-SO	0.07	0.06
RHA-WE	0.79	0.00
RHA-WP	1.43	0.05
Health Status in the two years before index date		
Consultation	0.35	0.10
Biochemistry, Transaminase (S.G.P.T)	0.72	0.05
Radioassays – T.S.H	0.74	0.02
Hematology, Counts, Blood, White Cell Count	0.56	0.01
Biochemistry, High Density Lipoprotein Cholesterol - HDL	0.89	0.03
Biochemistry, Lipids, Triglycerides	0.88	0.03
Biochemistry, Lipids, Cholesterol, Total	0.79	0.02
Biochemistry, Glucose, Quantitative	0.75	0.07
Biochemistry, Creatine	0.44	0.00
Hematology, Glycosylated Hemoglobin – HGB A1	0.62	0.09

Table B4. Comparison of Baseline Characteristics. Hospitalizations Outcome.

	Unweighted Standardized Differences	**IPT-Weighted Standardized Differences**
Characteristics at baseline		
Age	0.41	0.19
Distance to Care	1.23	0.03
Sex	0.03	0.12
Income Quintile Q1	0.18	0.18
Income Quintile Q2	0.06	0.14
Income Quintile Q3	0.02	0.04
Income Quintile Q4	0.08	0.07
Income Quintile Q5	0.25	0.07
RHA- IE	0.02	0.08
RHA- NO	0.55	0.06
RHA-SO	0.10	0.05
RHA-WE	0.75	0.04
RHA-WP	1.24	0.09
Health Status in the two years before index date		
Hospital Care – Per Day	0.30	0.27
After Hours Premium – Weekend Days	0.35	0.17
After Hours Premiums - 5:00 pm to 12:00 am	0.31	0.13
Special call to Emergency Room or OPD of a hospital	0.37	0.15
Consultation	0.35	0.02
Electrocardiogram, Interpretation and Report by Physician who did not take tracing 12 LDS	0.24	0.22
Biochemistry, High Density Lipoprotein Cholesterol - HDL	0.81	0.07
Biochemistry, Lipids, Cholesterol, Total	0.75	0.06
Biochemistry, Lipids, Triglycerides	0.81	0.08
Radiology Computerized axial tomography abdomen and/or pelvis exam	0.22	0.13

Appendix B.2: IPTW-Adjusted Effect of Telemedicine. General Case Including Low Users.

Table B5. IPTW-Adjusted Effect of Telemedicine. General Case Including Low Users

	N	Incidence-rate	95 % CI
Ambulatory Visits	233,892 (N1=8,443)	1.35*** (0.05)	1.26 1.44
Visits to Primary Care Practitioners	228,852 (N1=8,235)	1.28*** (0.05)	1.19 1.37
Visits to Specialists	149,513 (N1=6,793)	1.38*** (0.10)	1.20 1.60
Hospitalizations	73,380 (N1=5,770)	1.16 (0.13)	0.93 1.45

Notes: Significance at α= 0.01, 0.05, and 0.1 is denoted by ***, **, and *, respectively. Standard error in parenthesis. N1 denotes telemedicine patients.

Appendix B.3: Measuring Prevalence of Chronic Conditions

Table B6. Measuring Prevalence of Hypertension and Diabetes

Chronic Condition	Hospital Abstracts	Medical Services	Drug Program Information network
Hypertension	one or more hospitalizations with a diagnosis of hypertensive disease (ICD-9-CM: 401-405 OR ICD-10-CA: I10-I13, I15); or	one or more physician claims for hypertensive disease (prefix=7, ICD-9-CM: 401-405); or	one or more prescriptions for antihypertensive drugs, diuretics, beta blocking agents, calcium channel blockers, agents acting on the renin-angiotensin system, or terazosin with the following ATC codes: C02AB01, C02AB02, C02AC01, C02CA04, C02CA05, C02DB02, C02DC01, C02LA01, C02LB01, C03AA03, C03BA04, C03BA11, C03CA01, C03CA02, C03CC01, C03DA01, C03DB01, C03DB02, C03EA01, C07AA02, C07AA03, C07AA05, C07AA06, C07AA12, C07AB02, C07AB03, C07AB04, C07AB07, C07AG01, C07BA05, C07BA06, C07CA03, C07CB03, C08CA01, C08CA02, C08CA04, C08CA05, C08CA06, C08DA01, C08DB01, C09AA01, C09AA02, C09AA03, C09AA04, C09AA05, C09AA06, C09AA07, C09AA08, C09AA09, C09AA10, C09BA02, C09BA03, C09BA04, C09BA06, C09BA08, C09BB10, C09CA01, C09CA02, C09CA03, C09CA04, C09CA06, C09CA07, C09CA08, C09DA01, C09DA02, C09DA03, C09DA04, C09DA06, C09DA07, C09DA08, C09DB02, C09XA02, C09XA52, C10BX03, G04CA03
Diabetes	one or more hospitalizations with a diagnosis of diabetes: ICD-9-CM code 250 or ICD-10-CA codes E10-E14, OR	two or more physician visits with a diagnosis of diabetes: prefix=7 and ICD-9-CM code 250, OR	one or more prescriptions for medications to treat diabetes, using the medication list for diabetes on page 338 of The 2013 RHA Indicators Atlas http://mchp-appserv.cpe.umanitoba.ca/reference//RHA_2013_web_version.pdf#Page=370&View=Fit

Appendix B.4: Descriptive Characteristics for Telemedicine users with high Intensity of Telemedicine Use

Table B7. Descriptive Characteristics for Telemedicine users with an Intensity of Telemedicine Use Index over 50%.

	Mean	**SD**	**Max**	**Min**
Age	56.81	17.29	98	18
Distance to Specialists' Services (km)	324.20	203.06	1009.3	0.30
COCI	0.56	0.30	1	0
	N	**%**		
Sex				
Female	2094	54.26%		
Male	1765	45.74%		
Income Quintile				
Q1	1139	29.83%		
Q2	843	22.07%		
Q3	862	22.57%		
Q4	655	17.15%		
Q5	320	8.38%		
Regional Health Authority				
Interlake-Eastern	315	8.21%		
Northern	990	25.79%		
Southern Health	391	10.18%		
Prairie Mountain	2035	53.01%		
Winnipeg	108	2.81%		

Appendix C. Supplemental Material for Chapter 3

Appendix C.1: Codes used for defining Quality of Care Indicators

Table C1. Codes used for defining Quality of Care Indicators

Indicator	Codes
Breast Cancer Screening	Mammogram Tariffs: 7098, 7099, 7104, 7110, 7111
Influenza vaccination	Influenza Vaccination Tariffs: 8791, 8792, 8799
Colon Cancer Screening	FOBT Tariff: 9374
Cervical Cancer Screening	PAP test Tariffs: 9795, 8498, 8470, 8495, 8496
Asthma care	Asthma Prevalence: Individuals with two or more prescription for Beta 2-agonists: ATC codes R03AA, R03AB or R03AC Long-term asthma control medications are defined as the following: • Inhaled corticosteroids (ATC code R03BA); • Leukotriene modifiers (ATC code R03DC); or • Adrenergics and other drugs for obstructive airway diseases (ATC code R03AK). Exclusions: COPD patients, as defined by one or more prescriptions for Ipratropium Bromide (ATC codes R01AX03, R03AK04, R03BB01).
Diabetes Care	Diabetes Prevalence: • one or more hospitalizations with a diagnosis of diabetes: ICD-9-CM code 250 or ICD-10-CA codes E10-E14, OR • two or more physician visits with a diagnosis of diabetes: prefix=7 and ICD-9-CM code 250, OR • one or more prescriptions for medications to treat diabetes, using the medication list for diabetes on page 338 of The 2013 RHA Indicators Atlas Optometrist/Ophthalmologist: MD Bloc 051, 053

Hospitalizations due to ACSC	Four ambulatory care sensitive conditions (Only most responsible diagnosis was used): • COPD (ICD9: 491, 492, 494, 496; ICD10: J41, J42, J43, J44, J47) • Asthma (ICD9: 493; ICD10: J45) • Congestive Heart Failure (ICD9: 402.01, 402.11, 402.91, 428, 518.4; ICD10: I50, J81) • Diabetes (ICD9: 250; ICD10: E10-E14)

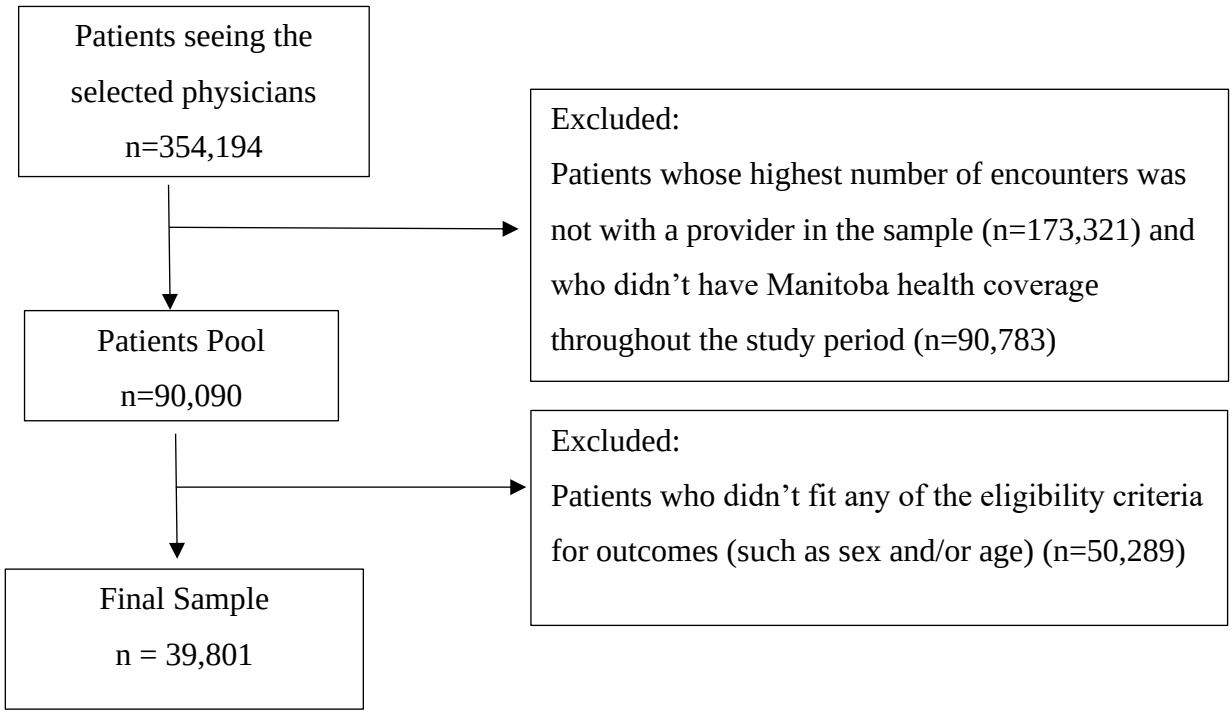
Appendix C.2: Tabulation of initial pool of PCP

Table C2. Tabulation of initial pool of PCP

cpcssn	***emr***	***nonemr***	**Frequency**	
0	0	0	886	
0	0	1	198	Non-EMR users
0	1	0	7	
0	1	1	251	
1	0	0	65	EMR users
1	0	1	9	
1	1	0	1	
1	1	1	62	

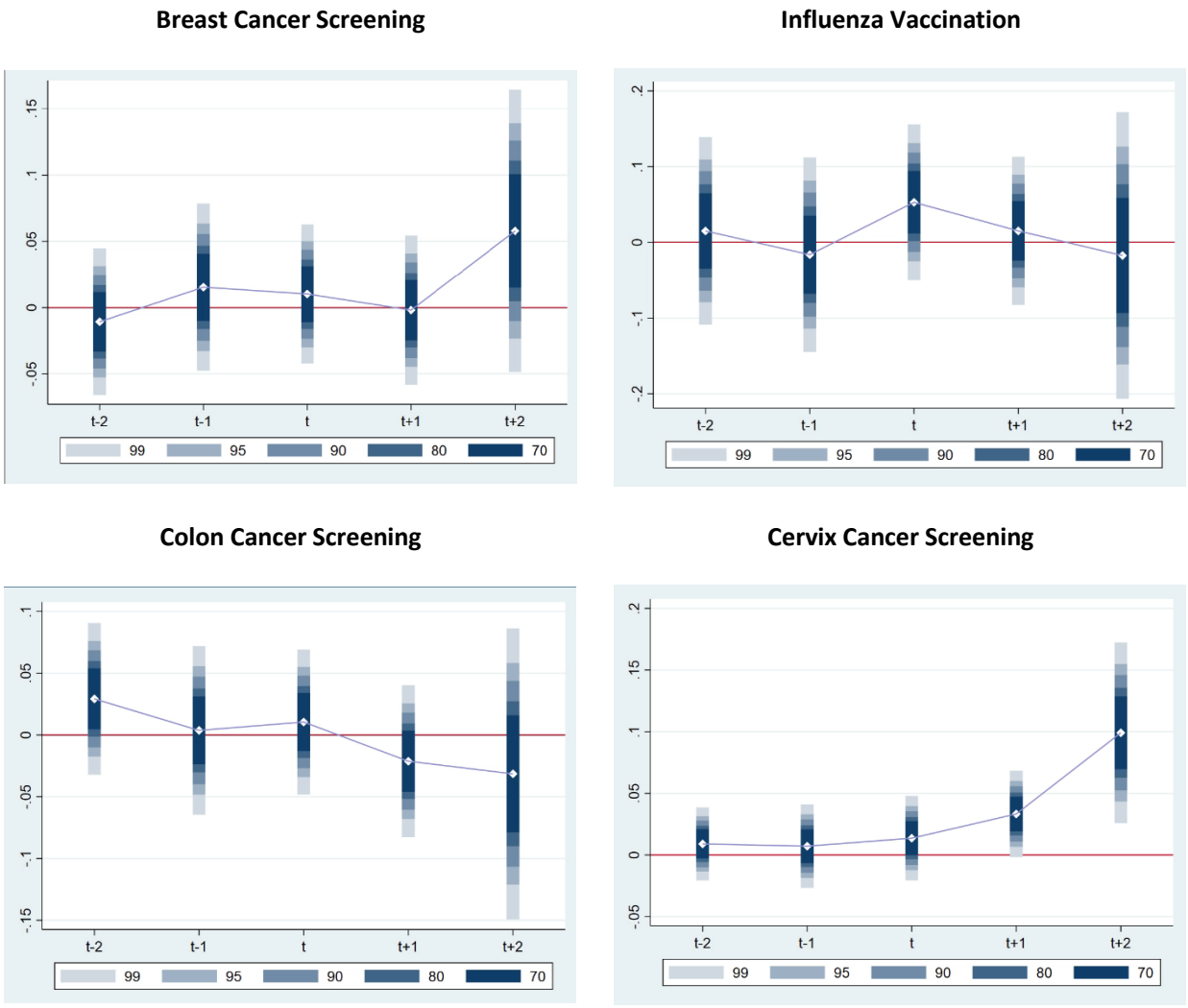
Appendix C.3: Cohort development for the sample of patients

Figure C1. Cohort development for the sample of patients

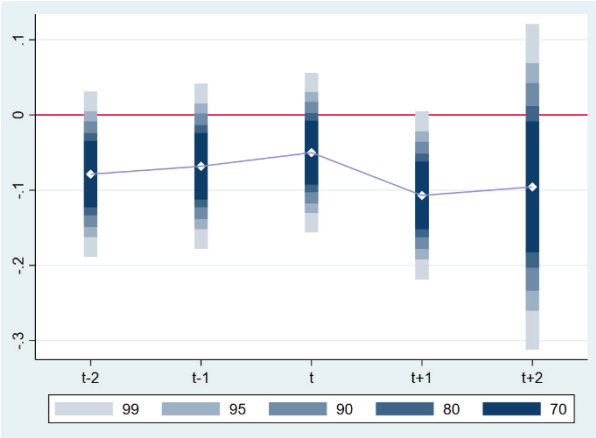


Appendix C.4: Time Effects Pre- and Post-EMR period for PCP

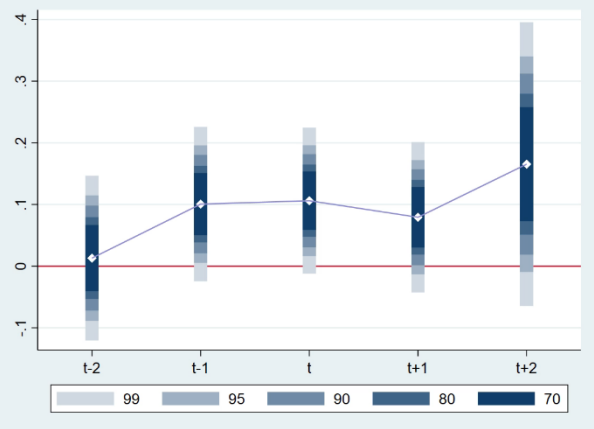
Figure C2. Time Effects Pre- and Post-EMR period for PCP by outcome



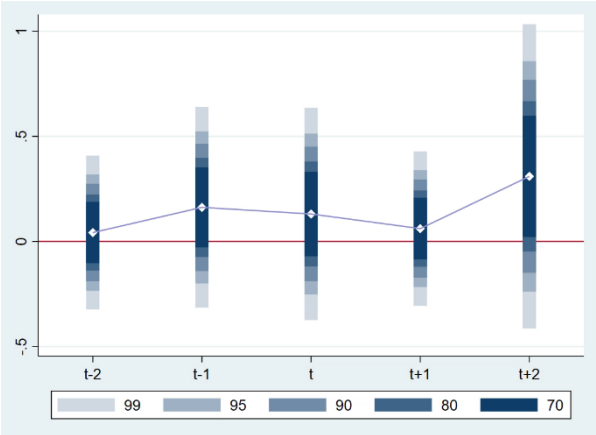
Ashtma Care



Diabetes Care



Hospitalizations ACSC



Note: Time effects are obtained from regressions as outlined in Eq. (5)

Appendix D. HREB Approvals

HREB Approval Chapter 2

UNIVERSITY OF MANITOBA | Research Ethics - Bannatyne
Office of the Vice-President (Research and International)

P126-770 Bannatyne Avenue
Winnipeg, Manitoba
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HEALTH RESEARCH ETHICS BOARD (HREB)
CERTIFICATE OF FINAL APPROVAL FOR NEW STUDIES
Delegated Review

PRINCIPAL INVESTIGATOR:	INSTITUTION/DEPARTMENT:	ETHICS #:
Elisabet Rodriguez Liorian	U of M/Economics	HS21298 (H2017:378)
APPROVAL DATE: November 21, 2017	**EXPIRY DATE:** **November 21, 2018**	
STUDENT PRINCIPAL INVESTIGATOR SUPERVISOR (If applicable): Dr. Gregory Mason and Dr. Janelle Mann		

PROTOCOL NUMBER:	PROJECT OR PROTOCOL TITLE;
NA	Economic Evaluation of Telemedicine Programs in Manitoba
SPONSORING AGENCIES AND/OR COORDINATING GROUPS: U of M Internal Funds	

Submission Date of Investigator Documents:	HREB Receipt Date of Documents:
October 18 and November 7, 2017	October 25 and November 9, 2017

THE FOLLOWING ARE APPROVED FOR USE:

Document Name	Version(if applicable)	Date
Protocol: Proposal including Clarifications as per Letter dated November 7, 2017		October 18, 2017
Consent and Assent Form(s):		
Other: Data Capture Sheet		submitted November 7, 2017

CERTIFICATION
The above named research study/project has been reviewed in a ***delegated manner*** by the University of Manitoba (UM) Health Research Board (HREB) and was found to be acceptable on ethical grounds for research involving human participants. The study/project and documents listed above was granted final approval by the Chair or Acting Chair, UM HREB.

HREB ATTESTATION
The University of Manitoba (UM) Research Board (HREB) is organized and operates according to Health Canada/ICH Good Clinical Practices, Tri-Council Policy Statement 2, and the applicable laws and regulations of Manitoba. In respect to clinical trials, the HREB complies with the membership requirements for Research Ethics Boards defined in Division 5 of the Food and Drug Regulations of Canada and carries out its functions in a manner consistent with Good Clinical Practices.

QUALITY ASSURANCE
The University of Manitoba Research Quality Management Office may request to review research documentation from this research study/project to demonstrate compliance with this approved protocol and the University of Manitoba Policy on the Ethics of Research Involving Humans.

CONDITIONS OF APPROVAL:

1. The study is acceptable on scientific and ethical grounds for the ethics of human use only. ***For logistics of performing the study, approval must be sought from the relevant institution(s).***
2. This research study/project is to be conducted by the local principal investigator listed on this certificate of approval.
3. The principal investigator has the responsibility for any other administrative or regulatory approvals that may pertain to the research study/project, and for ensuring that the authorized research is carried out according to governing law.
4. **This approval is valid until the expiry date noted on this certificate of approval. A Bannatyne Campus Annual Study Status Report** must be submitted to the HREB within 15-30 days of this expiry date.
5. Any changes of the protocol (including recruitment procedures, etc.), informed consent form(s) or documents must be reported to the HREB for consideration in advance of implementation of such changes on the **Bannatyne Campus Research Amendment Form.**
6. Adverse events and unanticipated problems must be reported to the HREB as per Bannatyne Campus Research Boards Standard Operating procedures.
7. The UM HREB must be notified regarding discontinuation or study/project closure on the **Bannatyne Campus Final Study Status Report**.

Sincerely,

[redacted]

Chair, Health Research Ethics Board
Bannatyne Campus

Please quote the above Human Ethics Number on all correspondence.
Inquiries should be directed to the REB Secretary **Telephone:** (204) 789-3255/ **Fax:** (204) 789-3414

Annual Reviews

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HEALTH RESEARCH ETHICS BOARD (HREB)

CERTIFICATE OF ANNUAL APPROVAL

PRINCIPAL INVESTIGATOR:	INSTITUTION/DEPARTMENT:	ETHICS #:
Elisabet Rodriguez Llorian	U of M/Economics	HS21298 (H2017:378)
HREB MEETING DATE (If applicable):	**APPROVAL DATE:** November 13, 2018	**EXPIRY DATE:** **November 21, 2019**
STUDENT PRINCIPAL INVESTIGATOR SUPERVISOR (If applicable): Dr. Gregory Mason and Dr. Janelle Mann		

PROTOCOL NUMBER:	PROJECT OR PROTOCOL TITLE:
NA	Economic Evaluation of Telemedicine Programs in Manitoba
SPONSORING AGENCIES AND/OR COORDINATING GROUPS: U of M Internal Funds	

Submission Date of Investigator Documents:	HREB Receipt Date of Documents:
November 21, 2017 (Signed October 26, 2018)	September 28, 2018

REVIEW CATEGORY OF ANNUAL REVIEW: **Full Board Review** ☐ **Delegated Review** ☒

THE FOLLOWING AMENDMENT(S) and DOCUMENTS ARE APPROVED FOR USE:

Document Name(if applicable)	Version(if applicable)	Date

Annual approval

*Annual approval implies that the most recent **HREB approved** versions of the protocol, Investigator Brochures, advertisements, letters of initial contact or questionnaires, and recruitment methods, etc. are approved.*

Consent and Assent Form(s):

CERTIFICATION

The University of Manitoba (UM) Health Research Board (HREB) has reviewed the annual study status report for the research study/project named on this ***Certificate of Annual Approval*** as per the category of review listed above and was found to be acceptable on ethical grounds for research involving human participants. Annual approval was granted by the Chair or Acting Chair, UM HREB, per the response to the conditions of approval outlined during the initial review (full board or delegated) of the annual study status report.

HREB ATTESTATION

The University of Manitoba (UM) Health Research Board (HREB) is organized and operates according to Health Canada/ICH Good Clinical Practices, Tri-Council Policy Statement 2, and the applicable laws and regulations of Manitoba. In respect to clinical trials, the HREB complies with the membership requirements for Research Ethics Boards defined in Division 5 of the Food and Drug Regulations of Canada and carries out its functions in a manner consistent with Good Clinical Practices.

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HEALTH RESEARCH ETHICS BOARD (HREB)

CERTIFICATE OF ANNUAL APPROVAL

PRINCIPAL INVESTIGATOR:	INSTITUTION/DEPARTMENT:	ETHICS #:
Elisabet Rodiguez Llorian	U of M/Economics	HS21298 (H2017:378)
HREB MEETING DATE (If applicable):	**APPROVAL DATE:** November 12, 2019	**EXPIRY DATE:** **November 21, 2020**
STUDENT PRINCIPAL INVESTIGATOR SUPERVISOR (If applicable): Dr. Gregory Mason and Dr. Janelle Mann		

PROTOCOL NUMBER:	PROJECT OR PROTOCOL TITLE:
NA	Economic Evaluation of Telemedicine Programs in Manitoba
SPONSORING AGENCIES AND/OR COORDINATING GROUPS: U of M Internal Funds	

Submission Date of Investigator Documents:	HREB Receipt Date of Documents:
November 21, 2017 (Signed September 24, 2019)	September 26, 2019

REVIEW CATEGORY OF ANNUAL REVIEW: **Full Board Review** ☐ **Delegated Review** ☒

THE FOLLOWING AMENDMENT(S) and DOCUMENTS ARE APPROVED FOR USE:

Document Name(if applicable)	Version(if applicable)	Date

Annual approval

*Annual approval implies that the most recent **HREB approved** versions of the protocol, Investigator Brochures, advertisements, letters of initial contact or questionnaires, and recruitment methods, etc. are approved.*

Consent and Assent Form(s):

CERTIFICATION

The University of Manitoba (UM) Health Research Board (HREB) has reviewed the annual study status report for the research study/project named on this ***Certificate of Annual Approval*** as per the category of review listed above and was found to be acceptable on ethical grounds for research involving human participants. Annual approval was granted by the Chair or Acting Chair, UM HREB, per the response to the conditions of approval outlined during the initial review (full board or delegated) of the annual study status report.

HREB ATTESTATION

The University of Manitoba (UM) Health Research Board (HREB) is organized and operates according to Health Canada/ICH Good Clinical Practices, Tri-Council Policy Statement 2, and the applicable laws and regulations of Manitoba. In respect to clinical trials, the HREB complies with the membership requirements for Research Ethics Boards defined in Division 5 of the Food and Drug Regulations of Canada and carries out its functions in a manner consistent with Good Clinical Practices.

HREB Approval Chapter 3

UNIVERSITY OF MANITOBA | Research Ethics and Compliance

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HEALTH RESEARCH ETHICS BOARD (HREB)
CERTIFICATE OF FINAL APPROVAL FOR NEW STUDIES
Delegated Review

PRINCIPAL INVESTIGATOR:	INSTITUTION/DEPARTMENT:	ETHICS #:
Dr. Gregory Mason	U of M/Economics	HS22719 (H2019:131)
APPROVAL DATE: March 22, 2019	**EXPIRY DATE:** March 22, 2020	
STUDENT PRINCIPAL INVESTIGATOR SUPERVISOR (If applicable): NA		

PROTOCOL NUMBER:	PROJECT OR PROTOCOL TITLE;
NA	The impact of EMR facilitated primary care on health outcomes (Linked to H2017:378)
SPONSORING AGENCIES AND/OR COORDINATING GROUPS: Thorlakson Foundation	

Submission Date of Investigator Documents:	HREB Receipt Date of Documents:
March 2 and March 18, 2019	March 5 and March 20, 2019

THE FOLLOWING ARE APPROVED FOR USE:

Document Name	Version(if applicable)	Date
Protocol: Proposal including Clarifications as per Letter dated March 18, 2019		submitted March 18, 2019
Consent and Assent Form(s):		
Other: Data Capture Sheet (Undated)		submitted March 2, 2019

CERTIFICATION
The above named research study/project has been reviewed in a ***delegated manner*** by the University of Manitoba (UM) Health Research Board (HREB) and was found to be acceptable on ethical grounds for research involving human participants. The study/project and documents listed above was granted final approval by the Chair or Acting Chair, UM HREB.

HREB ATTESTATION
The University of Manitoba (UM) Research Board (HREB) is organized and operates according to Health Canada/ICH Good Clinical Practices, Tri-Council Policy Statement 2, and the applicable laws and regulations of Manitoba. In respect to clinical trials, the HREB complies with the membership requirements for Research Ethics Boards defined in Division 5 of the Food and Drug Regulations of Canada and carries out its functions in a manner consistent with Good Clinical Practices.

QUALITY ASSURANCE
The University of Manitoba Research Quality Management Office may request to review research documentation from this research study/project to demonstrate compliance with this approved protocol and the University of Manitoba Policy on the Ethics of Research Involving Humans.

CONDITIONS OF APPROVAL:

1. The study is acceptable on scientific and ethical grounds for the ethics of human use only. ***For logistics of performing the study, approval must be sought from the relevant institution(s).***
2. This research study/project is to be conducted by the local principal investigator listed on this certificate of approval.
3. The principal investigator has the responsibility for any other administrative or regulatory approvals that may pertain to the research study/project, and for ensuring that the authorized research is carried out according to governing law.
4. **This approval is valid until the expiry date noted on this certificate of approval. A Bannatyne Campus Annual Study Status Report** must be submitted to the HREB within 15-30 days of this expiry date.
5. Any changes of the protocol (including recruitment procedures, etc.), informed consent form(s) or documents must be reported to the HREB for consideration in advance of implementation of such changes on the **Bannatyne Campus Research Amendment Form.**
6. Adverse events and unanticipated problems must be reported to the HREB as per Bannatyne Campus Research Boards Standard Operating procedures.
7. The UM HREB must be notified regarding discontinuation or study/project closure on the **Bannatyne Campus Final Study Status Report**.

Sincerely,

[redacted]

Chair, Health Research Ethics Board
Bannatyne Campus

Please quote the above Human Ethics Number on all correspondence.
Inquiries should be directed to the REB Secretary **Telephone:** (204) 789-3255/ **Fax:** (204) 789-3414

Appendix E. HIPC Approvals

HIPC Approval Chapter 2

Health, Seniors and Active Living
Health Information Privacy Committee
4040-300 Carlton Street, Winnipeg, Manitoba, Canada R3B 3M9
T 204-786-7204 **F** 204-944-1911
www.manitoba.ca

December 19, 2017

Elisabet Rodriguez Llorian
University of Manitoba
13-75 Killarney Avenue, Winnipeg, MB R3T 3B1
rodrig21@myumanitoba.ca

HIPC No. 2017/2018 – 48
File number to be quoted on correspondence

Re: Economic Evaluation of Telemedicine programs in Manitoba

Dear Elisabet,

The Health Information Privacy Committee has considered and ***approved*** your request for access to data for the purposes of the above named project.

Any significant changes to the proposed study design should be reported to the Chair/HIPC for consideration in advance of their implementation. Also, please be reminded that any manuscripts and presentation materials resulting from this study must be submitted to Manitoba Health, Seniors and Active Living for review. Specifically, manuscripts must be submitted *at least **30** calendar days* prior to the intended publication and presentation materials must be submitted *at least **10** calendar days* prior to the presentation.

Researcher Agreement will need to be completed before work on this project can commence. This will be initiated by **MCHP**. If you have any questions or concerns, please do not hesitate to contact [redacted], Committee Coordinator at ([redacted]

Yours truly,

[redacted]
Chair, Health Information Privacy Committee

c.c. [redacted]

Manitoba
spirited energy

HIPC Approval Chapter 3

Manitoba
Health, Seniors and Active Living
Health Information Privacy Committee
4040-300 Carlton Street, Winnipeg, Manitoba, Canada R3B 3M9
T 204-786-7204 F 204-944-1911
www.manitoba.ca

May 28, 2019

Gregory Mason
Department of Economics, University of Manitoba
557 Fletcher Argue Building, University of Manitoba
Winnipeg, MB R3T 5V5
gregory.mason@umanitoba.ca

HIPC No. 2019/2020 – 07
File number to be quoted on correspondence

Re: The impact of EMR facilitated primary care on health outcomes

Dear Dr. Mason,

The Health Information Privacy Committee has considered and ***approved*** your request for access to data for the purposes of the above named project.

Any significant changes to the proposed study design should be reported to the Chair/HIPC for consideration in advance of their implementation. Also, please be reminded that any manuscripts and presentation materials resulting from this study must be submitted to Manitoba Health, Seniors and Active Living for review. Specifically, manuscripts must be submitted *at least 30 calendar days* prior to the intended publication and presentation materials must be submitted *at least 10 calendar days* prior to the presentation.

Researcher Agreement will need to be completed before work on this project can commence. This will be initiated by MCHP. If you have any questions or concerns, please do not hesitate to contact [redacted], Committee Coordinator at [redacted]

Yours truly,

[redacted]
Chair, Health Information Privacy Committee

c.c. [redacted]

Manitoba
spirited energy