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Cost Estimation and Health Benefits Determinants of Medical Innovations Across Canadian Provinces

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Abstract

Against the historical backdrop of costly advances in medical technology driving up aggregate health care cost increases across high-income countries, this paper raises a fundamental question: can the high costs of medical innovations be justified when evaluated against the public health benefits of the innovations? In this paper, we offer an answer to this question using a two-step empirical methodology applied to pooled data across Canadian provinces over the period 1980-2014. We estimate the health care cost increases due to medical innovations using a residual-based approach and evaluate the ability of the residual-based cost estimates of medical innovations to explain log-level and the growth rates of four separate public health indicators, including life expectancy at birth, life expectancy at age 65, preventable deaths and infant mortality. We verify the sensitivity of our findings across three separate estimation methods: Pooled-least squares, bias-corrected pooled-GLS and pooled-system estimation methods.

Keywords: medical innovations, costs, benefits, bias correction, system estimation

1. Introduction

During the past six decades, high-income countries such as Canada, have invested heavily in costly medical innovations in order to prolong peoples' lives, reduce death and morbidity. Many well-known health economists have confirmed that the costs of advances and diffusion of medical technologies have been a primary driver of the rapid long-term growth in aggregate health care cost in these countries (Newhouse, 1992; Landon et al., 2013; Smith, 2016). The persistent growth in health care cost at a pace faster than the growth of GDP has strained both public and private budgets and put increasing pressures on policy makers to either curb the growth in health care costs, or continue to shift real resources from valuable alternative uses into the health care sector (Landon et al., 2013). The ongoing ageing of population and the Financial Crisis of 2007-2008 have further exacerbated these pressures and have prompted researchers to express serious concerns about the sustainability of these trends in the future (Skinner & Rovere, 2011; Lee, 2007; Pammolli et al., 2009).

Against the historical backdrop outlined above, this paper raises a fundamental question: can the high costs of medical innovations be justified when evaluated against the public health outcomes of the innovations? A formal investigation of this question at the aggregate (national/state/provincial) level is important for several reasons. First, the results of a macroeconomic evaluation of the cost effectiveness of medical innovations can guide future policies governing the optimal allocation of resources between the health care and other competing sectors (education, other government services). Second, many micro-studies have shown that the health benefits of specific medical interventions are significantly greater than their costs, see Neumann and Weinstein (1991) and the references cited therein. However, to our knowledge, no one to date has attempted to study the implications for the economy-wide aggregate effects of these micro-effects of medical innovations. Our analysis of the cost-effectiveness of aggregate medical innovations can shed light on whether the evidence from micro-studies, in fact, translate into similar cost effectiveness of medical innovations at the aggregate level. A final reason for the need of an aggregate study of the cost effectiveness of medical innovations is that previous research has paid surprisingly little attention to this important issue.

The paucity of research noted above is traceable to a lack of an effective empirical methodology for evaluating the aggregate costs of medical innovations against the multifaceted health benefits of the innovations. A key complicating factor is that the costs of aggregate medical innovations are not directly observable. Existing macro-studies have tried resolving this issue by simply using a time trend or some other proxy variable to

replace the role of technology; but these studies generally focus only on the cost of technology in medicine, ignoring the health benefits of medical technology (see section 2 for details).

We employ a novel two-step empirical strategy to evaluate the cost-effectiveness of aggregate medical innovations (see section 3 for details). Since the cost increases due to aggregate medical innovations are not directly observable, we rely on an indirect residual-based approach to estimate these cost increases.

Then, we evaluate the extent to which these estimated residuals (from step one) can explain the public health benefits of medical technology (Esmail & Wrona, 2008). Health researchers have long known that medical innovations (new drugs, new treatments, new devices, new social media support for healthcare, etc.) promote public health by enhancing life expectancy at different age groups and reducing mortality. In this paper, we assess the health benefits of medical innovations by examining their effects on both the level and the growth rate of several public health indicators including, life expectancy at birth, life expectancy at age 65, preventable deaths and infant mortality.

To demonstrate that the proposed two-step approach is an effective approach for dealing with the macroeconomic estimation problem at hand, we apply it to evaluate the cost effectiveness of medical innovations across the provinces of Canada over the period 1980-2014. While the same methodology is also applicable across countries, this involves an unavoidable trade off. On the one hand, medical data are clean and comparable across the Canadian provinces, but such data not directly comparable across countries (Gerdtham & Jonsson, 2000); on the other hand, there is likely to be less variability of medical innovations across provinces than across countries.

We recognize that our two-step approach to the evaluation of the cost-effectiveness of medical innovations raises the issue of generated regression problem (Murphy & Topel, 1985; Pagan, 1984). The problem is that the estimated residuals from the cost equation have a variance of their own; therefore, the using the residuals as an explanatory variable in the health benefit equations violets the requirement of being fixed in repeated samples. This means that the least squares estimator is likely to underestimate the standard error of the parameter estimates in the benefits equations, leading to findings statistical significance where there are not any.

To correct for this bias, we re-estimate the costs and benefits equations for medical innovations using two other estimation methods. The first of these is the pooled GLS estimator (Hoffman, 1987) and the second is the pooled system estimator. In the case of the GLS estimator, we estimate the benefits equations using the pooled instrumental variable (IV) estimator, with cross-section random effects and the EGLS options. In the latter case, we cast the cost and the benefit equations as a system of equations, and estimate them simultaneously. Our specification in this case ensures that the residuals from the cost equation automatically enter as an explanatory variable in the benefits equations. We compare the results across the three estimation methods, focusing on the effect of costs of medical innovations on the public health benefits of such innovations.

The rest of the paper runs as follows. Section 2 briefly describes the background literature relevant to this paper. In section 3, we present the study design, including data characteristics, data sources, data transformations, and models and econometric methodology. Section 4 reports the estimation results and residual analysis. Finally, section 5 concludes the paper and highlights its limitations.

2. Background Literature

In this section, we briefly review the theoretical and empirical literature relating to costs or benefits or both of advances in medical technology with a view to illuminate what the present paper adds to the existing literature.

A long time ago, economist Baumol (1967) predicted that expenditure on healthcare in rich countries would persistently grow more rapidly than expenditures on other goods and services. He based this prediction on three plausible observations. First, labor productivity in the health care sector grows at a much smaller pace than that in the progressive sector (rest of the economy). Second, health care providers receive the same wage increases as employees in the progressive sector. Third, consumers regard health services as a necessity with low price elasticity of demand. The first two observations imply that the provision of healthcare in these countries suffers from a 'cost disease' i.e., a persistent excess of wage over labor productivity growth; while all three observations taken together imply that the share of healthcare spending in GDP must continue to grow in the long run.

Many years later, Hall and Jones (2007) offered an explanation why rational people might willing pay for the rapid growth in health care costs that Baumol had predicted. These authors argue that as people get richer and their consumption of non-health goods and services rises over time, the marginal utility of consumption declines rapidly. As a result, people respond by being willing to spend more on R&D in health, in order to extend life to enjoy additional periods of utility.

Following Baumol's prediction, a large body of empirical research has investigated the sources for the rapid trend-growth in aggregate healthcare costs; a somewhat smaller body of work has examined the public health benefits of medical innovations and their diffusion. For convenience, we classify these studies into three separate groups. Group 1 covers research that account for the sources of the trend growth in health care costs, including medical innovations; Group 2 includes research that focus on the determinants of public health outcomes, including medical innovations and Group 3 examines research that encompasses both the costs and the health benefits of medical innovations and their diffusion.

2.1 Group 1 - The Costs of Aggregate Medical Innovations

Many studies, at the national level, have decomposed the per-capita health care cost increases into a portion accounted for by observable non-technology determinants and a portion attributable to advances in medical technology. Some of the studies have taken a direct approach to account for the contribution medical technology to aggregate health care costs. These studies have used a proxy for aggregate technology, such as a time trend (Di Matteo, 2005); fixed and time effects (Bates & Saunterre, 2013); or health care R&D spending (Okunade & Murthy, 2002). Others estimate the costs of aggregate medical innovations indirectly; they first estimate the contributions of all the non-technology drivers of the trend growth in per-capita health care costs and attribute the residual to advances in medical technology (Newhouse, 1992; Cutler, 1995; Smith, Heffler, & Freeland, 2000).

Despite many differences in models and methodology, a consistent set of conclusions have emerged from the empirical studies cited above. First, technological change in medicine is the most important driver of spending increases over time. For example, Newhouse (1992) could only explain less than half of the spending increases by non-technology factors; he, therefore, attributes more than 50 percent to technological change. Peden and Freeland (1995) attribute about two-thirds of spending increases from 1960 to 1993 to technological change. Smith, Heffler, and Freeland (2000) and Cutler (1995) also attribute substantial portions of spending increases to technological change. Okunade and Murthy (2002) finds support for Newhouse's conclusion that "technological change is a major escalator of health care expenditure." Di Matteo (2005) uses a time trend to proxy technological change and estimates that it accounts for 62 percent of the increase in spending. Second, growth in income is also an important driver of cost increases; however, other factors such as population aging play only a minor role.

2.2 Group 2 - Health Benefits of Medical Innovations

A relatively smaller set of studies have formally investigated the public health benefits of medical innovations compared to those that have examined the costs of such innovation. These studies generally recognize that public health production is complicated and does not depend solely on spending on health care (including medical innovations). Rather, health also depends on a host of other non-medical determinants including socio-economic, demographic, environmental, and lifestyle variables (Baltagi, Moscone, & Tosetti, 2012; Cutler et al., 2006; Shaw, Horrace, & Vogel, 2005; World Health Organization, 1991; 2001).

In recent years, a strand of the public health production literature has forcefully argued that access to social services (affordable housing, nutritional support for women, infants, children and adults and outreach programs) is a more important determinant of population health than health care itself. These services are a form of preventive healthcare that reduces the health risks to the broader population, rather than treating those with disease (McDaid et al., 2015). Researchers in this strand of the literature argue that sustained long-term growth in healthcare spending (including medical innovations) have exhausted most of the easy medical interventions to extend life and reduce death, thereby depressing the marginal health impact of health care spending below that of spending on social services.

Evidence from several studies has confirmed the relative importance of social services for population health (Bradley et al., 2011; Bradley et al., 2016; McDaid et al., 2015; Dutton et al., 2018). More specifically, the evidence from these studies shows the ratio of social services to health care spending is associated with higher life expectancy at birth and lower mortality rates in models that control for income, gender, population aged 65 and over and other non-medical determinants of health. This strand of the literature recommends a policy of shifting the composition of government budgets more towards social services and away from health care to achieve better health outcomes, without requiring an increase the size of the budget. Yawney and Faroque (2020) offer a cautionary note on the proposed policy shift.

2.3 Group 3 - The Costs and Health Benefits of Medical Innovations

Unlike the large literature on either the costs (Group 1) or the benefits (Group 2) of advances in medical

technology, only a handful of studies have examined both the costs and benefits of aggregate medical innovations simultaneously (Murphy & Topel, 2006; Viscusi, 1993). Economists Kevin Murphy and Robert Topel have taken such an encompassing approach and have evaluated the social benefits and costs of aggregate medical innovations in the USA over the period 1970-1990. Murphy and Topel first estimate what an average American would be willing to pay for a reduction in mortality risk that would add a year to his/her life. Using data on workers' pay in occupations with differing risks of job-related death, they derive an estimate of about $150,000 for an additional life-year, a figure that varies with age. Then, using age-dependent values of an additional year of life and the actual increases in average life expectancy over this period, Murphy and Topel attribute a value of about $2.8 trillion per year to the increased life expectancy. To put this figure in perspective, improvements in life expectancy over the period 1970-1990 contributed about 50-100 times what America spends annually on medical research.

Our paper contributes to the handful of studies in Group 3 that consider both the costs and benefits of advances in medical technology. As outlined in the introduction of the paper, however, our methodology differs markedly from those used in the existing literature. Instead of estimating the value of an extra year of life, we seek to answer the question of whether the high costs of medical innovations and their diffusion are associated with significant benefits for a wide variety of population health indicators. These health indicators include life expectancy at birth, life expectancy at age 65, preventable death, and infant mortality across the provinces of Canada.

In Section 3 below, we describe our benchmark models to estimate the aggregate costs of medical innovations and the models of public health benefits against which we evaluate the costs of medical innovations.

3. Study Design

3.1 Data, Sources, Variables and Transformations

Based on the literature review in section 2, we have assembled provincial data on health care expenditure, four health indicators and eleven potential determinants of health and health care expenditure over the period 1980-2014. One of the key requirements time series analysis is that all data should be stationary, meaning that the mean and the covariance structure should be invariant over time. In order to stabilize the covariance structure of the data, we follow the usual practice of taking the log-transformation of all continuous variables. Taking the log-transformation of all continuous variables also allows us to interpret the estimated parameter as the partial elasticity of the dependent variable with respect to the explanatory variable of model to which it is attached. The type of transformation needed to stabilize the mean of the variables depends on whether the mean changes in a perfectly predictable or in a random (unpredictable) way. In the former case, a simple time-trend suffices to capture the changing mean; in the latter case, taking first differences of variables stabilizes the mean of the variables.

3.2 Mean Stationarity Tests

To determine whether the variables are trend or difference stationary, we apply three separate unit root/stationarity tests to each of the sixteen-selected variable: the Augmented Dickey-Fuller (ADF), Phillip-Perron (PP) and the Kwiatkowski-Phillips-Schimdt-Shin (KPSS) tests. The null hypothesis for both the ADF and the PP tests is that the variable under investigation contains a random trend (is difference stationary), against the alternative hypothesis that the variable is trend stationary. In contrast, the null hypothesis for the KPSS test is that the variable is stationary (around a time trend) and the alternative is that the variable is non-stationary.

In Table 1 below, we present the results of all three tests, along with the definitions of the variables, the notations we use for each variable in the rest of the paper and the data sources. The results reported in Table 1 show that of the sixteen pooled variables, there is agreement across all three tests that the log-levels of five of the variables are stationary, four are non-stationary (difference stationary) and for the remaining seven variables the evidence is contradictory across the three tests. The evidence leaves us no clear choice about whether we should conduct our analysis in terms of log-levels or in growth rates (first-differences of the log-level) of the variables. Given the relatively large number of variables whose stationarity status is uncertain, in the next section, we present evidence both for log-levels and growth rates of the variables.

Table 1. The Augmented Dickey-Fuller (ADF) and Phillip-Perron (PP) unit root tests and the Kwiatkowski-Phillips-Schimdt-Shin (KPSS) stationarity test of the variables. Provincial Pooled Data: 1980-2014

Variable Description	(Notation)	ADF Test P value	PP Test P value	KPSS Test LM Stat.
Log health expenditure per capita	LHE	0.0227*	0.0663	0.0237*
Log disposable income per capita	LY	0.0002*	0.0013*	0.0343*
Log consumer price index	LCPI	0.0028*	0.0029*	0.0252*
Log population prop. aged 65+	LP65	0.0004*	0.0004*	0.1408*
Log unemployment rate	LUR	0.6300	0.6190	0.2055
Baumol Cost-desease Variable	B	0.0102*	0.0000*	0.0268*
Residuals from cost equation 1	RESIDS	0.0000*	0.0000*	0.0320*
Log Life expectancy at birth	LLE0	0.3699	0.1787	0.0245
Log Life expectancy at age 65	LLE65	0.3036	0.3016	0.0249
Log premature death	LPM	0.3737	0.4221	0.1113*
Log infant mortality	LIM	0.1268	0.0246*	0.0764*
Log real social services expenditure	LSS	0.1278	0.1195	0.1863
Log real expenditure on Tobacco	LTOB	0.0362*	0.9156	0.1651
Log real expenditure on Alcohol	LALCO	0.4644	0.5352	0.1763
Log poverty rate	LPR	0.0000*	0.0000*	0.0757
Log urbanization rate	LURBAN	0.8351	0.8805	0.2244
Log proportion of women	LSEX	0.0082	0.9821	0.0911

Note. * indicates rejection of the null at 5% significance level. The asymptotic critical values of the KPSS statistic are 0.216, 0.146 and 0.119 at the 1%, 5% and 10% levels respectively (Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1).

3.3 Econometric Procedures and Models

As we have noted in the introduction, we employ a two-step strategy to evaluate the cost-effectiveness of aggregate medical innovations in Canada. In step one; we use provincial pooled data to estimate the annual cost increases due to advances and diffusion of medical technology across Canadian provinces over the period 1980-2014. Since cost increases due to aggregate medical innovations are not directly observable, we employ an indirect residual-based approach (Solow, 1956) to estimate such cost increases (Smith, 2016; Newhouse, 1992). Following this approach, we first estimate the (per-capita) health care cost increases due to all observable non-technology determinants of such cost increases (e.g., income growth, ageing population, price inflation, insurance coverage and others). We then attribute the residuals – the portion of the annual provincial health care cost increases not accounted for by these explanatory variables to innovations and diffusion of medical technology. We save these residuals (RESIDS) from step one, for use in step-two estimation.

Our residual-based estimates of the provincial cost increases due to medical innovations are based on the estimation of a model that accounts for the growth in provincial per-capita growth in health care costs, as shown in equation (1) below. Bates and Santerre (2013) and Colombier (2017) have employed similar models to account for the growth in health care costs at the national level:

$$\Delta(\log(HEPC_{it})) = f(\Delta(\log Y)_{it}, \Delta(\log(CPI)_{it}, \Delta(\log(POP65)_{it}, \Delta UR_{it}, REC_{it}, \Delta(INEQUALITY)_{it} + (RESIDS)_{it} \quad (1)$$

$$i = 1, 2, 3, \ldots, 10 \quad \text{and } t = 1, 2, 3, \ldots, 34$$

The dependent variable of equation (1) is the growth in per-capita healthcare expenditure in province i and year t. The province-specific explanatory variables shown on the right-hand-side of equation (1) include all of the non-technology determinants of the growth in per-capita healthcare spending. In particular, they include the growth in per-capita GDP, growth in CPI inflation, growth in population aged 65 years and over, changes in the unemployment rate, a dummy variable for provincial recession dates and changes in the rate of inequality. The estimated residuals from equation (1), $\widehat{RESID}it$, denote our residual-based estimates of the contribution of medical innovations to aggregate healthcare cost increases in province i and year t.

Next, we analyze the multi-dimensional health benefits of medical innovations by evaluating the marginal impact of the variable $\widehat{RESID}it$ on four different public health indicators. We specify each of the four health indicators as a function of expenditure on medical innovations (residuals from step one) and other non-medical determinants of public health, including socio-economic, demographic and lifestyle variables. For purposes of illustration, we write down the most general model for the health indicator as shown in equation (2) below:

$$\Delta \ln(HI_j)it = \beta_0 + \beta_1(\widehat{RESIDS})_{it} + \beta_2 \Delta\ln(SS)_{it} + \beta_3 \Delta \ln(GNI)_{it} + \beta_4 \Delta\ln(UN)_{it} + \beta_5 \Delta ln(AGE65)_{it} + \beta_6 \Delta ln(URBAN)_{it} + \beta_7 \Delta ln(ALCO)_{it} + \beta_8 \Delta ln(TOBC)_{it} + \varepsilon_{it} \quad (2)$$

where j = 1, 2, 3, 4

where the dependent variable $\Delta\ln(HI_j)$ is the growth rate of the jth health indicator and HI_1 = life expectancy at birth; HI_2 = life expectancy at age 65; HI_2 = premature and preventable death; HI_4 = infant mortality. The province-specific explanatory variables on the right-hand-side of equation (2) include the estimated residuals, $(\widehat{RESIDS})_{it}$, from equation (1) and other non-technology determinants of public health. These include the growth of per-capita real expenditure on social services, the growth in per-capita real income, the growth in the unemployment rate, growth in population aged 65 years and over, growth in urbanization, growth in per-capita spending on alcohol and the growth in per-capita spending on tobacco. The parameter of primary interest to this paper is the coefficient β_1 attached to the variable $(\widehat{RESIDS})_{it}$, which measures the marginal effect of the aggregate costs of all health innovations in province i and year t on the public health indicator j, where j = 1, 2, 3, 4. The sign, size and significance of the estimated coefficient β_1 across the four health indicator models determine the public health benefits of medical innovations in Canada. This enables us to draw tentative inferences about the cost-effectiveness of medical innovations in Canada.

We use provincial pooled data from 1980 to 2014 to estimate equations 1 and 2. Initially, we estimate equations 1 and 2 separately, using the least square (LS) estimator. However, because we use the residuals (RESIDS) from equation 1 as an additional explanatory variable in equation 2, the latter equation suffers from a generated regression problem (Murphy & Topel, 1985; Pagan, 1984). Consequently, the LS estimator may underestimate the standard errors of the parameters of equation 2, leading to finding of statistical significance where there is not any.

To correct for this bias, we re-estimate equation 2 using two other estimation methods. The first of these is the pooled GLS estimator and the second is the pooled system estimator. In the case of the GLS estimator, we estimate equation 2 using the pooled instrumental variable (IV) estimator, with cross-section random effects and the EGLS options (Note 1). In the latter case, we cast equations 1 and 2 as a system of equations, and estimate them simultaneously.

4. Results

4.1 Results for Log-Levels of the Variables

In Table 2, we report the estimation results for log-levels of the variables. This includes the regression output for the costs of healthcare (equation 1) and the benefits of medical innovations (equation 2) for all four health indicators using three estimators: pooled least squares (pooled-LS), pooled instrumental-variable generalized LS (pooled-IV-GLS) and the pooled system (pooled-system) estimation methods.

The left-most column of Table 2 shows the explanatory variables, while the next column shows the estimation results for the healthcare costs (equation 1) using the pooled-LS estimator. We use the residuals (RESIDS) from this equation as an additional explanatory in each of the four public health indicator models (equation 2) only for the pooled-LS and pooled-IV-GLS estimators, which we report in the third and fourth columns from the left respectively. The last column documents the estimation results from simultaneously estimating equation (1) and equation (2) using the pooled system estimation method.

Before examining the details, two general comments about the overall goodness-of-fit of the costs (equation 1) and the benefits (equations 2) of medical innovations are in order. First, we consider the healthcare cost equation 1 in column 2 (from the left) of table 2. As can be seen from the bottom of the column, the adjusted-R^2 metric shows that only about 42 percent of the year-to-year variation in provincial per-capita healthcare costs is explained by the observable non-technology factors. The associated Durbin-Watson (DW) statistic indicates absence of serial correlation, which lends credibility to the estimated adjusted-R^2 value. The unexplained 58 percent of the variation is the maximum attributable to advances and diffusion of medical technology and other excluded factors from our model. To put this estimate in perspective, Newhouse (1992) attributes less than 50 percent, while Smith, Heffler and Freeland (2000) attribute nearly two-thirds of the variation to medical technology. We use the residual series (RESIDS) from equation 1 as an additional explanatory variable in the health indicators equation (2).

Second, consider now the estimated benefits medical innovations confers on each of the public health indicators (equation 2) reported in the third, fourth and fifth columns (from the left) of table 2. The adjusted-R^2 metric for each of the four health-indicator models across all three-estimation methods range from 49 percent to 81 percent, with a mean of 67 percent, indicating that the overall explanatory power of the health indicator models is substantial. The associated values of the Durbin-Watson (DW) statistic generally indicate absence of serial correlation, which suggests that the goodness of fit of the models indicated by the adjusted-R^2 metric is unlikely to be the result of 'spurious correlation' (Granger & Newbold, 1974). This, in turn, means that the life expectancy and mortality rates estimated across three estimation methods are highly credible.

Third, we report the results of the RESET test at the bottom table 2. The RESET test tests the null hypothesis that there is no non-linearity in equations 1 and 2. The p-values for the test do not reject the null hypothesis in the majority of the cases at the 5 percent significance level. Thus, linear specification of the costs and benefits equations for medical innovations seem adequate in most of the cases.

We now examine some interesting details regarding the estimated effects of the individual determinants of public health. We begin with the variable of primary interest to us – the residuals from the cost equation 1 (RESIDS), denoting the costs of medical innovations. Since we have used the residuals (RESIDS) from equation 1 as an explanatory variable only for the pooled-LS and pooled-IV-GLS estimators, we consider these results reported in the third, fourth columns (from the left) of table 2.

It is clear from the sign and significance of the estimated coefficient attached to the RESIDS variable that investment in medical innovations significantly increases the average life expectancy at birth, as well as at age 65, under both the least squares and the bias-corrected IV-GLS estimation methods. Furthermore, medical innovations also significantly decreases preventable death and infant formality under both the least squares and the bias-corrected IV-GLS estimation methods. The only difference between the two estimators is the quantitative size of the estimated effects; the size of the increases in life expectancy (at birth and at age 65) are bigger under the pooled-IV-GLS estimation method than the corresponding increases under the pooled-LS estimation method. The same is also true for the mortality rates; the quantitative size of deceases in preventable deaths and infant mortality are bigger under the pooled-IV-GLS estimation method than the decreases under the pooled-LS estimation method.

In is noteworthy that the estimated health benefits of medical innovations under the bias-corrected pooled-system estimator (see the last column of table 2) generally reinforce the corresponding health benefits estimated under the bias-corrected IV-GLS estimation method. Both the IV-GLS and the system estimation methods significantly increase life expectancy (at birth and at age 65) and both decrease mortality (preventable and infant); the difference arises only in the fact that the quantitative size of the increase in life expectancy and the decrease in mortality are smaller under the system estimator. Thus, the overall evidence documented in table 2 strongly supports the commonly held view that advances in medical technology and their diffusion have multi-faceted health benefits in terms augmenting life expectancy and reducing mortality rates.

Table 2. Cost (equation 1) and benefit (equation 2) of health innovations estimation results. Variables are in log-levels. Number of Jurisdictions = 9, Number of Years = 32. Number of Observations = 288

Estimator	Pooled-LS		Pooled-LS			Pooled-IV-GLS				Pooled-System			
	Equation1		Equation2			Equation2				Equations 1 and 2			
	LHE	LLE0	LLE65	LPD	LIM	LLE0	LLE65	LPD	LIM	LLE0	LLE65	LPD	LIM
Constant	0.002[a]					0.360[b]	0.263[b]	-0.051	0.261	0.002	0.002	0.002	0.001
	(0.00)					(0.05)	(0.04)	(0.85)	(0.28)	(0.21)	(0.39)	(0.51)	(0.83)
LY	0.042[a]									0.343[a]	0.343[a]	0.342[a]	0.341
	(0.00)									(0.00)	(0.00)	(0.00)	(0.25)
LCPI	0.245[c]									0.665[a]	0.664[a]	0.665[a]	0.664
	(0.07)									(0.00)	(0.00)	(0.00)	(0.13)
LP65	-0.002									-0.008	-0.008	-0.006[a]	-0.005
	(0.77)									(0.85)	(0.90)	(0.00)	(0.97)
REC	-0.004									0.001	0.003	0.002	-0.001
	(0.44)									(0.95)	(0.97)	(0.98)	(0.99)
LHE(-1)	0.362[a]									0.362[a]	0.362[a]	0.363[a]	0.362
	(0.00)									(0.00)	(0.00)	(0.00)	(0.18)
LUR	-0.004[a]												
	(0.01)												
RESIDS		0.029[b]	0.076[b]	-0.109[a]	-0.780[b]	0.492[b]	1.033[b]	-1.764[b]	-4.72[c]	0.075[c]	0.122[b]	-0.151[b]	-0.456[b]
		(0.05)	(0.05)	(0.00)	(0.02)	(0.05)	(0.05)	(0.03)	(0.10)	(0.06)	(0.03)	(0.03)	(0.02)
LTOB		0.005[b]	0.006[b]	-0.044[a]	-0.095[a]	0.016[a]	0.037[a]	-0.082[a]	-0.12[b]				
		(0.03)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.05)		0.019[a]	-0.022[a]	-0.025
LALC		-0.01[a]	-0.033[a]	0.033[a]	0.075[b]	-0.013[a]	-0.027	0.134[b]	0.32[b]		(0.00)	(0.00)	(0.34)
		(0.00)	(0.00)	(0.00)	(0.02)	(0.00)	(0.35)	(0.02)	(0.04)	-0.011[b]	-0.032[a]	0.014	0.070
LPR			-0.016			-0.061[c]			0.469	(0.10)	(0.00)	(0.06)[b]	(0.39)
			(0.44)			(0.09)			(0.45)			0.051[a]	0.131[c]
LURBAN				0.047[c]	0.091[b]							(0.00)	(0.09)
				(0.08)	(0.03)								

LRSS		0.005[c]	0.017[b]					-0.053	-0.20[c]	-0.231[a]	-0.382	-0.018	
		(0.08)	(0.03)					(0.14)	(0.08)	(0.00)	(0.39)	(0.16)	
LSEX		-0.093								0.009[b]	0.009		0.085
		(0.22)								(0.09)	(0.26)		(0.81)
LP65			0.996[a]					0.774[a]					
			(0.00)					(0.00)		-0.031	-0.249[a]		
LLE0(-1)		0.712[a]				0.804[a]				(0.56)	(0.00)		
		(0.00)				(0.00)							
LLE65(-1)										1.257[a]			
										(0.00)			
LPD(-1)					0.615[a]							1.209[a]	0.487[a]
					(0.00)							(0.00)	(0.00)
LIM(-1)					0.029[b]				0.957[a]				0.797[a]
					(0.00)				(0.00)				(0.00)
ADJ. R^2	0.42	0.81	0.80	0.82	0.63	0.49	0.62	0.62	0.34	0.68	0.67	0.83	0.63
SE OF REG.	0.001	0.00	0.01	0.02	0.07	0.01	0.02	0.03	0.09	0.01	0.02	0.02	0.07
DW STAT.	2.09	1.68	2.24	1.58	1.44	2.09	2.00	2.14	2.53	1.05	1.04	1.25	2.49
RESET		0.01	0.00	0.14		0.95	0.73		0.34			0.09	0.05
(P-value)													

Source: Authors' calculations using data from the Canadian Institute of Health Information (CIHI), CANSIM, and Federal Reserve Economic Data – FRED-St. Louis Fed.

Note. P-values reported in parenthesis; a-significant at 1% level; b-significant at 5% level; c- significant at 10% level.

Besides medical innovations, Table 2 also provides evidence that a number of other determinants of health have significant effects on the average life expectancy and the mortality rates of Canadians across the provinces. Among these, the most important is the availability of community-based social services; services such as affordable housing, nutritional support for women, infants, children and outreach programs markedly increase life expectancy and help reduce mortality. The evidence also shows that the poverty rate consistently reduces life expectancy and increases mortality rates. Overall, the evidence documented in table 2 seems to be in accord with the strand of the literature that has previously emphasized the importance of social services for population health (Bradley et al., 2011; Bradley et al., 2016; McDaid et al., 2015; Dutton et al., 2018).

Our final comment on table 2 refers to the health effects of two life-style variables included in our model: log-levels of real per-capita expenditure on alcohol consumption (LALC) and real per-capita expenditure on tobacco (LTOB). The evidence clearly shows that alcohol reduces life expectancy and increases mortality; but, somewhat surprisingly, the effects of tobacco are generally not significant at the standard five percent significance level.

4.2 Results for Growth Rate of the Variables

Table 3 reports the estimation results for the growth rates (first-difference of the log-levels) of the variables. In this table, we summarize the regression output for the per-capita growth in costs of healthcare (equation 1) and the growth in benefits of medical innovations (equation 2) for the same four health indicators using the same pooled-LS, pooled-IV-GLS and the pooled-system estimation methods.

It is instructive to compare the results in table 3 (growth rates) with those in table 2 (log-levels) of the variables. The first notable difference between estimation in log-levels and in growth rates shows up in the goodness-of-fit of the costs and benefits models (equations 1 and 2) for medical innovations. The adjusted-R^2 for equation 1 is now somewhat higher (47 percent compared to 42 percent) (see, column 2 from left of table 3). Therefore, the cost attributable to medical innovations is now somewhat smaller (53 percent compared 58 percent). Nevertheless, the opposite is true for the estimated health benefits (equation 2) across the three estimation methods. The adjusted-R^2 is markedly lower for each health indicator and estimation method, with an average value of only 10 percent compared to the table 2 average value of 67 percent. In all likelihood, this simply reflects the difficulty of explaining the changes in growth rates of life expectancy and mortality compared to explaining changes in their log-levels of the variables.

Turning to the health effects of RESIDS – the variable of primary interest to this paper, the evidence in table 3 reinforces the findings from table 2. The results show that, medical innovations markedly increase the (growth rate of) life expectancies at birth and at age 65, and significantly decrease the (growth rate of) preventable deaths and infant mortality across all three estimation methods. Thus, we conclude this paper with a belief that the two-step empirical methodology used here is credible and is applicable to estimate the costs of aggregate

medical innovations and evaluate the multi-faceted public health benefits of medical innovation at the provincial, state or national level.

Table 3. Estimation results for the Cost (equation 1) and benefits (equation 2) of medical innovations: Variables are in log-differences (growth rates). Number of jurisdictions = 9; Number of Years = 32; Number of pooled observations = 288.

Estimator	Pooled-LS	Pooled-LS				Pooled-GLS				Pooled-System			
	Equation1	Equation2				Equation2				Equations 1 and 2			
	GHE	GLE0	GLE65	GPD	GIM	GLE0	GLE65	GPD	GIM	GLE0	GLE65	GPD	GIM
Constant	0.006					0.057[a]	0.066	-0.251[a]	0.312	0.010[a]	0.016[a]	0.002	0.003
	(0.72)					(0.00)	(0.11)	(0.00)	(0.13)	(0.00)	(0.00)	(0.48)	(0.80)
G Y	0.374[a]				0.146	0.010[a]	0.058[a]	0.229[a]	0.546	0.288[a]	0.285[a]	0.343[a]	0.343
	(0.00)				(0.53)	(0.00)	(0.00)	(0.00)	(0.23)	(0.00)	(0.00)	(0.00)	(0.18)
G CPI	0.533[a]									0.174[b]	0.178[b]	0.448[a]	0.665[c]
										(0.04)	(0.05)	(0.00)	(0.08)
Δ (P65)	-0.001									-0.088[a]	-0.008	-.0.008	0.001
	(0.97)									(0.01)	(0.79)	(0.91)	(0.97)
Δ (UR)	0.055[a]												
	(0.00)												
REC	-0.003									-0.006[a]		0.000	-0.001
	(0.13)									(0.00)		(0.97)	(0.99)
GHE(-1)	0.328[a]									0.353[a]	0.007[a]	0.362[a]	0.362
	(0.00)									(0.00)	(0.00)	(0.00)	(0.12)
RESIDS		0.023[b]	0.068[a]	-0.165[b]	-0.684[a]	0.019[a]	0.054[b]	-0.286[a]	-3.232[b]	0.042	0.087[c]	-0.092[b]	-0.417[a]
		(0.06)	(0.06)	(0.05)	(0.01)	(0.00)	(0.05)	(0.00)	(0.02)	(0.43)	0.07)	(0.05)	(0.00)
GSEX						0.006	0.139[a]	0.473[a]	5.552[a]		-0.009[a]		
						0.047[a]	(0.00)	(0.00)	(0.01)		(0.00)		
GTOB		0.024[c]	0.066[c]	-0.081	-0.406[c]	(0.31)		0.007	-0.243	-0.038	-0.087	0.174[a]	0.137
		(0.07)	(0.08)	(0.26)	(0.07)	0.001[a]	-0.003	(0.58)	(0.37)	(0.21)	(0.43)	(0.00)	(0.22)
GALC		0.030	0.145[a]	-0.234[a]	-0.561[b]	0.007	(0.24)			0.036[c]	0.019	-0.165[a]	-0.495[a]
		(0.00)	(0.00)	(0.00)	(0.04)	(0.00)	0.006				(0.16)	(0.00)	(0.00)
GRSS		0.013[c]	0.041[b]	0.062[c]	-0.023	(0.24)	(0.24)	0.027[a]	-0.264[c]			0.079[a]	
		(0.06)	(0.04)	(0.08)	(0.83)	-0.005[a]		(0.00)	(0.07)			(0.00)	
GPR		-0.011	-0.036	0.090[b]	0.166	(0.00)				-009		0.049[c]	0.049
		(0.15)	(0.12)	(0.03)	(0.21)	0.000	0.002[a]		0.029[a]	(0.59)		(0.09)	(0.56)
GURBAN		-0.121	-0.331	0.606	2.657	(0.24)	(0.01)		(0.00)	-353[c]			
		(0.13)	(0.43)	(0.40)	(0.24)					(0.06)			
GLE0(-1)		0.096				0.283[a]				0.292[b]			
		(0.115)				(0.00)				(0.05)			
GLE65(-1)			0.086				0.271[a]				0.243[b]		
			(0.19)				(0.00)				(0.02)		
GPD(-1)				0.062[c]				-0.238[a]				0.062	
				(0.07)				(0.00)				(0.26)	
GIM(-1)					-0.398[a]				-0.400[a]				-0.397[a]
					(0.00)				(0.00)				(0.00)
ADJ. R^2	0.47	0.10	0.07	0.05	0.17	0.11	0.12	0.09	0.10	0.18	0.12	0.04	0.16
SE OF REG.	0.01	0.00	0.01	0.02	0.06	0.00	0.00	0.01	0.13	0.00	0.00	0.02	0.06
DW STAT.	2.13	1.98	2.01	2.01	2.09	2.02	2.01	1.98	2.34	2.01	2.05	1.99	1.99
RESET (P-value)		0.74	0.52			0.94	0.22					0.03	0.28

Source: Authors' calculations using data from the Canadian Institute of Health Information (CIHI), CANSIM, and Federal Reserve Economic Data – FRED-St. Louis Fed.

Note. P-values reported in parenthesis; a-significant at 1% level; b-significant at 5% level; c- significant at 10% level.

4.3 Residual Analysis

Residual analysis is relevant to all regression analysis. Perhaps it is particularly relevant to our particular application because we use the residuals from equation (1), RESIDS, as an explanatory variable in equation (2). Below, we present the time plot (Figure 1), distribution (Figure 2) and the Q-Q plot (Figure 3) of the RESIDS variable. These three charts together inform us about distributional properties of the residuals from equation 1 (RESIDS) and, therefore about the distributional properties of the dependent variable of equation 1 – the growth of per-capita provincial pooled health care expenditures.

A visual examination of Figure 1 and Figure 2 suggests that the series RESIDS has zero mean and constant variance and appears to have an approximately normal distribution. The results of the Jaque-Bera test reported in Figure 2, however, shows that the distribution of RESIDS is not exactly normal. It tests the joint null hypothesis that compared to the normal distribution; the excess skewness and the excess kurtosis in the distribution of RESIDS are zero. The p-value (0.002) rejects the joint null at the 5 percent significance level. Consequently, strictly speaking, the series RESIDS and the dependent variable do not come from a normal distribution. It is pertinent to note here a consequence of the central limit theorem in statistics is that for moderate to large samples, a violation of the normality assumption should not adversely affect the usual inferential procedures.

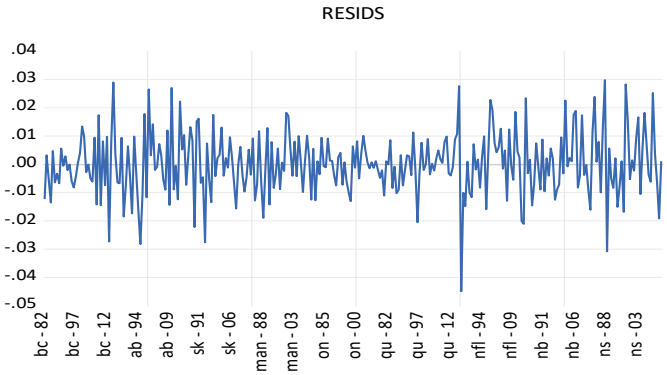

Figure 1. Time Plot of RESIDS

Figure 3 compares the quantiles of the standard normal distribution on the vertical axis (y) to the corresponding quantiles of the RESIDS series on the horizontal axis (x). If RESIDS are normally distributed, then all pairs of the points in the (x-y) space should lie along a line.

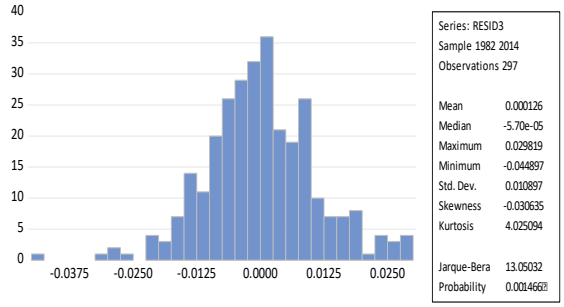

Figure 2. Distribution of RESIDS

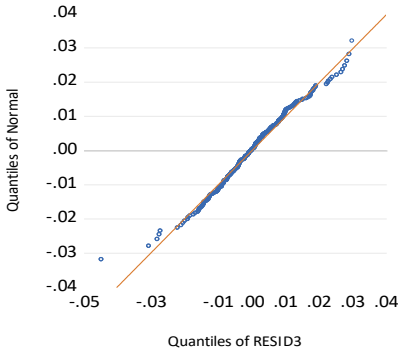

Figure 3. Q-Q Plot of RESIDS

An examination of Figure 3 reveals that almost all of the data points lie on or close to a straight line; only one point is somewhat removed of the line. Since this latter data point may or may not constitute an outlier, we conclude that there is no strong evidence of the presence of outliers in the RESIDS series.

5. Conclusions and Limitations

Against the historical backdrop of costly advances and diffusion of medical technology driving up growth in health care costs across high-income countries, the financial crisis of 2008, and an ongoing ageing population,

this paper raises a fundamental question: can the high costs of medical innovations be justified when evaluated against the public health benefits of the innovations? In this paper, we offer an answer to this question based on a two-step empirical methodology applied to pooled data across Canadian provinces over the period 1980-2014. Our analysis evaluates the ability of residual-based estimated costs of aggregate medical innovations to explain the level and growth rates of four separate health indicators of medical innovations (life expectancy at birth, life expectancy at age 65, preventable deaths and infant mortality) across three separate estimation methods: pooled-least squares, bias-corrected pooled-GLS and pooled-system estimation methods.

The primary finding of the paper is that investment in medical innovations and their diffusion have strong, multi-faceted public health benefits. They markedly increase the average life expectancies at birth and at age 65 and their growth rates. They also significantly decrease preventable deaths, infant mortality, and their growth rates. We conclude that the two-step approach used in the paper is a credible methodology for evaluating the cost-effectiveness of medical innovations in Canada and other high-income countries.

The findings of this paper are subject to two sources of limitations. First, the residual-based approach used in the paper is vulnerable to confounding technological change with omitted variables and other factors whose full contributions remain unaccounted in our model. For example, Amy Finkelstein (2007) shows that separating the effects of technology from health insurance coverage is problematic; this means that the residual-based contribution of technology would be smaller if expenditure on technology were not covered by insurance.

Second, some determinants of public health, such as consumption of tobacco, alcohol and social services, are likely to have long and variable lags. Since there is no available theory to guide the determination of optimal lags, one must rely on experimentation with alternative lag structures. Our experimentation with different lag structures has revealed that dynamic models generally perform better than static models. More importantly, the sign and significance of the coefficient attached to the residuals (RESIDS) variable are impervious to most lag structures across all three estimation methods, in a few cases; the statistical significance of the coefficient is sensitive to the lag structures.

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Note

Note 1. The instruments we use to estimate equation (2) with the GLS estimator include the growth of current and lagged values of the provincial house prices and the lagged values of the explanatory variables on the right hand side of equation (2), with the exception of the RESIDS variable.