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The potential socio-economic impact of telemedicine in Canada

Appendices

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Appendix A: Valuing tangible benefits of time gained through substituting in-person primary care visits by teleconsultations

In this appendix we provide more technical detail about the calculations of travel time lost due to in-person primary care consultations and provide the technical details about the macroeconomic model used to estimate the associated potential economic benefits of reduced travel time.

A.1. Calculating travel time lost per annum

In Section 4.1.1 we described some of the data used to calculate travel time lost for in-person appointments. In addition to the information presented in Chapter 4, Table A.1 and A.2 report additional data that has been used for the calculations, such as the total population, number of physicians per population and total number of consultations per year.

Table A.1: Key geographical statistics by province/territory, latest available data

	Population	Land area in km^2	Pop. density per km^2	All physicians	Physicians per 1,000 population	Physicians per 1,000 km^2
Canada	35,151,728	8,965,588	8.3	84,250	2.3	19.4
Newfoundland and Labrador	519,716	370,514	1.4	1,501	2.9	4.1
Prince Edward Island	142,907	5,686	25.1	289	2	50.8
Nova Scotia	923,598	52,942	17.4	2,481	2.7	46.9
New Brunswick	747,101	71,389	10.5	1,787	2.4	25
Quebec	8,164,361	1,356,625	6	20,680	2.5	15.2
Ontario	13,448,494	908,699	14.8	30,171	2.2	33.2
Manitoba	1,278,365	552,371	2.3	2,871	2.2	5.2
Saskatchewan	1,098,352	588,244	1.9	2,424	2.2	4.1
Alberta	4,067,175	640,330	6.4	10,143	2.5	15.8
British Columbia	4,648,055	922,503	5	11,742	2.5	12.7
Territories	113,604	3,496,285	0	161	1.4	0

Source: Canadian Census of Population 2016, Canadian Medical Association.

%

Table A.2: Number of physicians by specialisation and number of procedures by province, 2019

	Physicians per 1,000 population				Services per 1,000 population	
	Family medicine / general practice	Medical specialists	Surgical specialists	All physicians	Consultations and visits	Procedures
Canada	1.3	0.7	0.3	2.3	4,753	1,913
Newfoundland and Labrador	1.8	0.8	0.3	2.9	5,583	1,856
Prince Edward Island	1.2	0.5	0.3	2	2,934	1,582
Nova Scotia	1.4	0.9	0.4	2.7	3,758	1,315
New Brunswick	1.5	0.6	0.3	2.4	4,076	2,024
Quebec	1.2	1	0.3	2.5	4,909	1,417
Ontario	1.1	0.9	0.3	2.2	5,297	2,523
Manitoba	1.2	0.8	0.3	2.2	5,541	2,873
Saskatchewan	1.3	0.6	0.3	2.2	4,598	2,416
Alberta	1.4	0.9	0.2	2.5	6,557	1,932
British Columbia	1.4	0.9	0.3	2.5	5,750	2,423
Territories	1.2	0.1	0.2	1.4	3,284	686

Source: Canadian Institute for Health Information, National Physician Database, 2018–2019.

With the data available, we can construct a model for the estimation of costs savings are a result of time savings through TM. As discussed above, the savings are a function of time saved, formally:

$$tc_p = p_p \times s_p \times \left(2d_p \times t + w_p\right) \times a \qquad (3)$$

where tc_p are the total estimated time cost savings, by province, as a result of TM; p_p is the total population by province; s_p is the average number of health consultations and visits per 1,000 population; d_p is the average minimum distance to a healthcare facility; t is the travel time per kilometre travelled; w_p is the average wait time in the outpatient setting for their appointment to begin; and a is the average applicability of TM to the services considered measured by the share of total healthcare consultations that could possibly be replaced by teleconsultations (e.g. we assume only GP and nurse visits are applicable by TM, whereas visits to specialists are not substitutable by remote visits). The share of TM-applicable consultations is taken from data provided by the Canadian Community Health Survey 2017–2018 and reported in Table A.3.

Table A.4 summarises the model calibration using parameters discussed above. The average travel time per kilometer travelled is based on the spatial analysis partially presented in Figure 3.1, using a wide range due to high variance in transport types and environments, from relatively slow public transport or walking in cities to relatively fast car transport in rural areas. To be conservative in our calculations we assume two minutes per kilometer travelled, or 30 kilometers per hour.

Table A.3: TM applicability of all consultations by province/territory

Province	Parameter α
Newfoundland and Labrador	48.1
Prince Edward Island	47.1
Nova Scotia	42.9
New Brunswick	41.4
Quebec	55.3
Ontario	42.5
Manitoba	44.3
Saskatchewan	46.5
Alberta	39.4
British Columbia	34.6
Territories	39.7

Source: Canadian Community Health Survey 2017–2018.
Note: Parameter alpha represents the share of TM applicability (GP, nurse) among all consultations (e.g. specialist care).

Table A.4: Calibration of time-saving model at the province and territory level

Symbol	Parameter	Value	Reference
p_p	Total population	0.1–13.4 million	Table A.1
s_p	Health services per 1,000 pop.	3.2–6.6 thousand	Table A.2
d_p	Average min. distance to healthcare facility	8–133 kilometers	Table 4.3
t	Travel time per kilometer travelled	3 minutes	See text
w_p	Average appointment wait time	48 minutes	Table 4.3

A.2. The model of Canada's economy

A.2.1. Model structure

The model includes two main production sectors: healthcare services and all other goods and services. All final consumption (i.e. private, public, investment and net-exports) are aggregated into a single household account that demands healthcare and other goods and services. The aggregate household is endowed with capital and time that is used either as labour-supply or leisure. Some time is also wasted for buying goods and services, for example, households require travel time and waiting time before they actually receive healthcare services.

Our main aim is to quantify the economic and social value of introducing TM into the economy, and the main feature in this model is the labour-leisure component. In the counterfactual, we increase the level of TM, which reduces wasted time to obtain healthcare services. This 'freesup' and expands the number of leisure hours available and allows households to re-allocate time between more leisure and more labour. Leisure enters household's well-being directly, while an increase in the labour supply allows for more labour resources to raise production, lower production costs, raise household income and overall raise household's consumption of final goods and services.

The model is coded in GAMS, using MPSGE as a mixed complementarity problem (MCP). MPSGE is a non-mathematical sub-language that enables researchers to develop complex multi-level functions with ease, which also eliminates the many possible coding errors.

A.2.2. Supply of healthcare output and other goods

Production

Figure A.1: Production

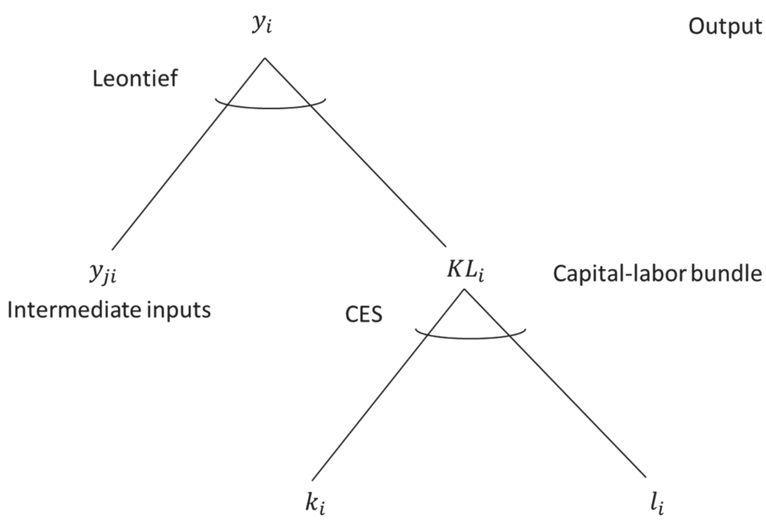


Figure A.1 describes the two-level production function used. The economy has two production sectors: healthcare and other goods defined by set $i = [health, other]$, with j alias to i. Output y_i is supplied at price p_i. Firm i maximises profits given a two-level, differentiable, constant return to scale (CRS) production function. In the lower-level, demand for capital k_i and labour l_i inputs, with cost-of-capital r and wage w, are combined into a composite factor through a Constant Elasticity of Substitution (CES) function[1]:

$$\begin{aligned} \max_{KL_i,k_i,l_i} \quad \pi_i^{KL} = & \quad p_i^{KL} KL_i - (r_i k_i + w_i l_i) \\ \text{s.t.} \quad KL_i \geq & \quad \delta_i F(k_i, l_i, \alpha_i, \sigma_{2i}) \end{aligned}$$

[1] For example, KL_i represents a functional form of $\delta_i F(k_i, l_i, \alpha_i, \sigma_{2i}) = \delta_i \left(\alpha_i^{\frac{1}{\sigma_{2i}}} k_i^{\frac{\sigma_{2i}-1}{\sigma_{2i}}} + (1-\alpha_i)^{\frac{1}{\sigma_{2i}}} l_i^{\frac{\sigma_{2i}-1}{\sigma_{2i}}} \right)^{\frac{\sigma_{2i}}{\sigma_{2i}-1}}$. Solving this type of problem is quite standard and made very easy with MPSGE. Note that when $\sigma \to 0$, the CES function converges to a Leontief (fixed shares) function, while when $\sigma \to 1$ it converges to a Cobb-Douglas (CD) function.

Furthermore, p_i^{KL} is the unit cost of the composite factor, σ_{2i} is the elasticity of substitution between labour and capital, α_i their share parameter, and δ_i a scaling factor. Finally, markets must clear with $K = \sum_i k_i$ and $L = \sum_i l_i$, i.e. the total-supply of capital and labour equals their demands (respectively).

In the top-level, the capital-labour value added, KL_i, is combined with intermediate inputs y_{ji} to form y_i, with $\mathcal{A}_{ji}$ their share parameters and σ_{1i} the substitution elasticity between them.[2]

$$\begin{aligned} \underset{y_i, KL_i, y_{ji}}{\text{Max}} \quad \pi_i = &\quad p_i y_i - \left(p_i^{KL} KL_i + \sum_j p_j y_{ji} \right) \\ \text{s.t.} \quad y_i \geq &\quad F\left(y_{ji}, KL_i, \mathcal{A}_{ji}, \sigma_{1i}\right) \end{aligned}$$

Household demand

The aggregate household demands healthcare services and other goods. The household's utility is a multi-level, continuous, function with two main components: (1) economic utility (consumption) C; and (2) overall utility U. The former is calibrated to the national accounts and includes an element of time cost (wasted time to reach medical services) and the latter includes the leisure component. The nested structure is provided below:

$$\begin{aligned} \underset{c_i, h_i, \mathrm{H}}{\text{Max}} \quad \mathrm{U} = &\quad F(C, H, \alpha_0, \sigma_0) \\ \text{s.t.} \quad \mathrm{C} = &\quad \rho_1 F(\widehat{c_i}, \alpha_1, \sigma_1) \end{aligned}$$

$$\widehat{c_i} = \rho_2 MIN(a_i c_i, \gamma_i b_i h_i$$

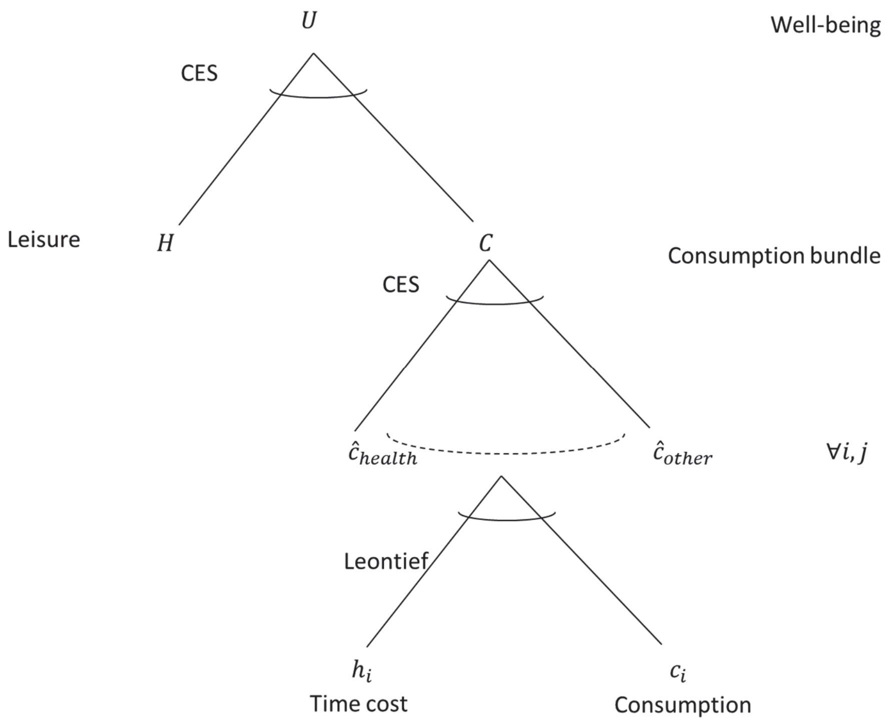
$$\sum_i (p_i c_i + w h_i) + wH = rk + w_{leisure} T$$

Figure A.2 below characterises graphically the household utility function.

Starting from the lowest level, households demand goods c_i, but waste a fixed proportion of time (hours) h_i to obtain these goods. a_i, b_i are the the weights of goods and time proportion. Furthermore, in the baseline scenario $sc = 0$, $\gamma_{i,0} = 1$ is a technology parameter set to one. In the counterfactual scenarios $sc \in [1, N]$, $\gamma_{health,sc} < 1$ is lowered according to the assumption on the improvements in TM, which would lower the wasted time required to obtain healthcare. As we do not change telecommunications for other sectors $\gamma_{other,sc} = 1$, we will simplify notation and omit the industry index i and focus only o n health, i.e. $\gamma_{health} = \gamma_{sc}$. The price of each good is p_i, the opportunity cost of wasted time is w and ρ_2 is a scaling parameter.

[2] Finally, the activities produced by the sectors are transformed into commodities. We omit a discussion here to save time, and especially as it is not important for describing the model, but rather used to fit the data to the model.

Figure A.2: Household utility function



In the second-level, goods and services are bundled together into C. The consumption bundle of c_i is a CES function of the goods $i = [health, other]$ with α_1 a weight parameter calibrated from the SAM, σ_1 a substitution parameter between health and other goods, and ρ_1 a scaling parameter. Finally, at the top-level, the household demands leisure time (hours) H and the consumption bundle C, which have an opportunity cost of w and unit-cost function p_C (i.e. the consumer price index of a bundle). α_0 is the weight of Leisure-Consumption and σ_0 a low-substitution between them.

The budget constraint is as follows. Households are endowed with capital K and a time endowment T, which is divided between labour-supply, leisure H and time cost h_i – discussed in the next section.

Labour-Leisure trade off

As mentioned above, the key feature of this model is enabling labour-supply to endogenously adjust to the household's choice between leisure and labour. To do this, households are endowed with amount T of time which they divide between leisure H, wasted-time h_i to obtain goods, and labour-supply L. We introduce a simple function L that transforms an amount of leisure into labour-supply L following:

$$L \geq 0, w_{leisure} - w \geq 0, L(w_{leisure} - w) = 0$$

where this equation is a complementarity function that says that if $L > 0$, households have converted some of their leisure time into labour up to a point where the value of leisure equals the wage rate, $w_{leisure} = w_{pri}$. If, however, the unit value of leisure is higher than the wage rate, $w_{leisure} > w$ (a strict inequality), the activity goes slack, $L = 0$ and no labour is generated.

In the baseline, only the proportion actually supplied to the market is observable, $L = \overline{L}$, a starting value. The value of T, H and h_i are unobservable in traditional national accounts, which we calibrate based on the assumptions discussed in the next section.

Finally, we need to specify an elasticity of substitution between leisure and consumption goods σ_1, which will in turn imply an elasticity of labour supply η. Currently, $\sigma_1 = 0.5$, which suggests a 'backward bending' labour-supply curve, which falls with an increase in the wage rate.[3]

A.2.3. Calibrating the healthcare model to Canada

To calibrate the model to Canada, we first construct a unique health-focused social accounting matrix (SAM) of Canada for the year 2017 (available upon request). This is a balanced table of incomes and expenditures across multiple aggregate national accounts. The SAM is constructed by incorporating the latest 2017 Supply and Use tables provided by Statistics Canada. The tables include 492 industry level disaggregation, of which 13 are health activities and nine are health commodities. We simplify the SAM by aggregating health activities and health commodities into two accounts and aggregating all other non-health activities and commodities into two non-health accounts.

Next, two additional non-observable accounts are added to the SAM that calibrate the monetary value of leisure and lost time. We estimate the overall monetary value of household's time endowment T in the following way. For a 24-hour period, Canadians sleep on average 6.5 hours and work 4.9 hours and therefore use 12.6 hours per day (on average) for leisure and wasted time. From the national accounts, the labour wage bill comes out at CAD 1,323bn and since labour-time is 28 per cent of time (excluding sleep), this implies that the monetary value of time is approximately T= CAD 4723bn. (Note that we assume that the hours of sleep is fixed and does not depend on our model.)

Next, to calibrate the baseline monetary value of lost time $h = w_{leisure,0} \cdot LT$, we require the implied average hourly value of leisure $w_{leisure,0}$ which is multiplied by the hours of lost time (LT) that we estimated in Table 4.4. $\mathrm{w_{leisure,0}} = \frac{M}{hrs} = \mathrm{CAD\ 47.52}$ is obtained by dividing the yearly average per capita income M by the total number of effective per-capita working hours hrs. The former, M, is obtained by dividing the wage bill (i.e. CAD 1,323bn) by the population in 2017 (i.e. 36.5m). The latter, hrs, is obtained by multiplying the average working days per year of 151 (i.e. 251 days weighted by the participation rate of 62%) by 4.9 average working hours per day. Thus, the monetary value of lost time is $\mathrm{w_{leisure}} \cdot \mathrm{LT} = \mathrm{h}$ at CAD 16.7bn.

Finally, the monetary value of leisure time H is CAD 3,384bn, which is the difference between the total value of time by the value of labour time and value of wasted time.

[3] With a $\sigma_1 = 1$ between consumption and leisure, labour-supply would be inelastic with respect to wage, while with $\sigma_1 > 1$, and increase in the wage rate will mean an increase in labour supply.

Appendix B: Healthcare cost savings associated with fewer emergency department visits and missed appointments

In this appendix we provide the technical details on how we calculated the estimated direct healthcare cost savings due to fewer emergency department visits and missed appointments.

B.3. Fewer emergency department visits

Technically, we can quantify the effect of fewer emergency department visits as follows:

$$ed_p = p_p \times e_p \times c_p \times a \times (ec - ss_p) \tag{1}$$

where ed_p are the total estimated savings due to fewer ED visits; p_p is the total population by province; e_p is the average proportion of non-urgent ED visits that could be treated through TM consultations instead; c_p is the average number of ED visits per person per year; a is the average applicability of TM to the services considered; ec is the average cost of an ED visit for the government; and ss_p is the average cost of a standard service (consultation or visit) that may replace the non-urgent ED visit (i.e. $ec - ss_p$ is the cost differential, per visit, of switching to standard healthcare services instead of ED visits).

We can calibrate each of these parameters using empirical data from population-representative surveys and academic literature presented in Tables 4.7-4.9 in the main report. For simplicity, we assume that the two reasons for ED visits that can be addressed through TM – wanting to see a professional sooner and not having a primary provider available at the time – are mutually exclusive. This has negligible effect on the results as only around 5 per cent of all respondents selected more than one reason for their ED visit.

One missing parameter is the overall applicability of TM α. To remain conservative in our modelling, we assume that only GP and nurse visits based on data from Table 4.6, would be replaced by TM (the remaining visits would require physical checks and would always need to be done in person). All other consultations and visits, ranging from various specialist assessments to hospital care days, are assumed to be unaffected by TM.[4]

The full parametrisation of the ED visits model is shown in Table B.1.

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[4] This is an oversimplification as some of the main areas of telemedicine use are e.g. in radiology (see Kane & Gillis 2018; Morozov et al. 2018). The estimated positive impact of telemedicine is therefore arguably understated.

Table B.1: Calibration of ED visits model at the provincial or territorial level

Symbol	Parameter	Value	Reference
p_p	Total population	0.1–13.4 million	Table A.1
e_p	Non-urgent ED visits	18%–36%	Commonwealth Fund Survey (2016)
c_p	Average number of ED visits per person-year	0.4–0.7	Table 3.8
ec	Average cost of ED visit	$124–$245	Brondani and Ahmad (2017)
ss_p	Average cost of a standard service	$46–$80	Table 3.8

Note that in the calculations presented in the main report we used the average value assumption for non-urgent ED visits and the average cost of and ED visit.

B.3. Fewer missed appointments

Technically, we can quantify the impact of fewer missed appointments as follows:

$$ma_p = p_p \times s_p \times mi_p \times o_p \times a \times ss_p \quad (2)$$

where ma_p are the total estimated savings due to fewer missed appointments; p_p is the total population by province; s_p is the average number of health services per 1,000 population; mi_p is the proportion of all appointments that are missed because of inability to travel, travel complications, insufficient time and other causes preventable through TM; o_p is the average proportion of such appointments that would have not been missed if TM was more accessible; a is the average applicability of TM to the services considered; and ss_p is the average cost of a standard service (consultation or visit) as reported in Table A.3. The model calibration using data presented in this section is summarised in Table B.2.

Table B.2 Calibration of the no-show model

Symbol	Parameter	Value	Reference
p_p	Total population	0.1–13.4 million	Table A.1
s_p	Health services per 1,000 pop.	3.2–6.6 thousand	Table A.2
mi_p	Preventable missed appointments (proportion of all appointments)	45%–64%	Claveau et al. (2020)
o_p	Reduction in preventable missed appointments	40%–74%	NHS England (2016)
ss_p	Average cost of a standard service	$46–$80	Table 3.8

Appendix C: Valuing the welfare effects for a lack of primary healthcare provider using the wellbeing valuation approach

C.1. How does the Wellbeing Valuation approach compare to other valuation methods?

Two valuation methods have been commonly applied to evaluate the willingness to pay for non-marketable goods at the individual level: (1) stated preferences; and (2) revealed preference methods (Frey et al. 2007). In this section we outline the strengths and weaknesses of these approaches and compare them to the Wellbeing Valuation approach.

The most prominent stated preferences method is contingent valuation. In a contingent valuation survey, individuals are asked how much they would be willing to pay to, for example, reduce crime (Brand & Price 2001). Several challenges tend to be associated with the approach:

- Primary data collection can be expensive and time consuming.
- Survey respondents may find themselves in unfamiliar situations and may be induced to give strategic responses.
- Applying contingent valuation to access to healthcare is not straightforward, especially about the preferences to evaluate, either in terms of gains or losses.

Revealed preference methods have been applied to various topics, mainly in environmental policy analysis. Revealed preference is a method which exploits the relationship between individual behaviour and associated environmental attributes to estimate the value of it. For example, one revealed preference approach typically used is the travel cost method. Here estimates make use of information about how much people implicitly or explicitly pay to visit locations with specific attributes, such as a cultural institution or a recreational area (Hicks 2002). Under certain circumstances an individual's willingness-to-pay can be inferred from these observations.

Another revealed preference approach is hedonic price regressions. These have been applied, for instance, to value school quality (Gibbons & Machin 2008). This method relies on there being a marketable good, such as housing, for which prices change with the quality of the non-marketed good, in this example school quality in the area or other public services. With regard to access to a healthcare provider, individuals could be willing to pay more for housing in an area of the city that has better healthcare facilities. The challenge with the hedonic price method is that it assumes that markets (e.g. housing) are more or less perfect, which would only apply if households or individuals have full information about the market, if there was sufficient supply in a market (e.g. people can freely move houses without constraints), and if there were low transaction costs (e.g. costs related to moving). These conditions seldom hold in reality – and friction exists – which makes the application of the hedonic price method often more difficult to justify.

Stated and revealed preference methods are generally well implementable if specific data are available (in terms of type and quality). They have reporting biases and stated preference approaches tend to be quite costly in terms of data collection in certain applications.

While the previous paragraphs have highlighted the main strengths and limitations of the approaches, Table 4.13 summarises them and adds some further limitations associated with each approach.

Table C.1: Methods to value non-marketed goods; strengths and weaknesses

Stated Preferences	Revealed Preferences	WVA Approach
Based on survey questions to elicit willingness-to-pay (WTP) for provision of a non-marketed good in a hypothetical situation	Based on real choices made by individuals; assumes that the preferences of individuals can be revealed by their purchasing habits	Based on micro-econometric happiness functions to elicit willingness-to-pay for non-marketed goods; assumes subjective-well-being is a proxy for individual utility or welfare
Relative ease of technical implementation	Based on economic theory	Based on economy and psychological theory; wide range of applications
Wide range of applications, also allow measurement of value where other non-market valuation methods are not valid, i.e. measurement of non-use values	Based on real choices rather than hypothetical scenarios	Relatively cost-efficient; no need for specific data collection No individual response bias as individuals do not respond to hypothetical scenarios
Require carefully designed survey and sampling procedures	Limited set of applications; not able to evaluate non-use values	Based on econometric specifications which only show correlation and not causation
Relative costly; substantial investment of time and resources	Assumes markets are (almost) perfect	Relies on publicly available survey data
Individual response bias; analysis based on hypothetical situations	Depending on application need for large and high-quality data	

Source: RAND Europe.

C.1. How the approach is implemented empirically

The empirical approach taken can be described in simple terms as follows: in a first step one estimates the association between lack of access to healthcare providers to both income and individual life satisfaction. In a second step, one estimates the necessary income (or so-called 'compensating income variation') which would be needed in order to counteract or compensate for the reduced life satisfaction from not having a healthcare provider available in the local area. In more technical terms, in the first step, we define micro-econometric happiness functions using measures of life satisfaction as outcome measures, relating this to a set of control variables, including income. In a second step, we calculate a so-called 'compensation variation' for measuring the value of providing access to a healthcare provider for individuals that have not one in their area. We describe both steps in more detail in what follows.

C.1.1. Micro-econometric happiness functions

The first step is essentially based on estimating the following baseline (linear) empirical specification[5]:

$$LS_{irt} = \beta_0 + \beta_1 HC_{it} + \beta_2 Inc_{irt} + \beta_3 X_{irt} + \delta_r + \gamma_{rt} + \varepsilon_{irt} \quad (1)$$

In this equation, the variables are defined as follows:

- $\boldsymbol{LS_{irt}}$: denotes the self-reported subjective well-being of individual *i* living in location *r* at time *t*. It serves as a measure of the individual utility.
- $\boldsymbol{HC_{it}}$: denotes an indicator measuring a reported lack of access to healthcare for an individual at time *t*. This represents a barrier to access to adequate healthcare. Note that if we expect that lack of access to healthcare has a negative impact on an individual's life satisfaction, we would expect the parameter β_1 to be negative.
- $\boldsymbol{Inc_{irt}}$: denotes the (log) level of household income for individual *i*, in location *r* at time *t*. If the level of income has an expected positive impact on an individual's subjective well-being we would expect the parameter β_2 to be positive.
- $\boldsymbol{X_{irt}}$: represents a vector of control variables usually applied in measuring determinants of happiness including, among others, personal characteristics of individual *i*, such as education level, gender, age, job situation or marital status. It also contains control variables that are correlated both with life satisfaction and income and/or lack of healthcare provider is important in order to reduce the issue of omitted variable bias. We elaborate in more detail below which control variables have been included in the analysis.
- $\boldsymbol{\delta_r}$: are time-invariant region-specific effects, controlling for factors that do not change over time within specific regions, such as specific geographical characteristics.
- $\boldsymbol{\gamma_t}$: are time-specific effects, that are common across regions including for instance Canada-specific changes in GDP or other time-varying shocks.

Calculating the compensating income variation

In a second step, we use the parameter estimates β_1 and β_2 from estimating equation (1) to estimate the compensating income variation for not having access to a healthcare provider. Following Frey et al. (2009), we measure the compensating income variation (CIV) which is the estimated decrease in income necessary to hold utility (proxied as life satisfaction) constant. Technically, the second step of the CIV approach assumes that self-reported life satisfaction is a proxy for utility or welfare and estimates a utility function, U, which depends positively on household income, *y*, and negatively to a lack of access to a healthcare provider, *HC*. As outlined in equation (2), the so called 'compensating variation' for not having access to a healthcare *CIV* is obtained by equating utility in a state 0 (with healthcare provider) with individual utility in state 1 (without healthcare provider):

$$U^0(y^0, HC^0) = U^1(y^0 - CIV, HC^1) \qquad (2)$$

Using the linear happiness function, and the parameters from equation (1), including the vector of control variables *X* as outlined above, *CIV* can be written as a function of a change in the level of access to a healthcare provider ΔHC as reported in (3):

[5] Using either Ordinary Least Squares (OLS) or since the outcome variable is on a Likert-Scale between 0 and 10 also using non-linear Ordered Logit (OL). Previous empirical research suggests that the findings are robust against the choice of estimation method. Given that both we include a large set of fixed effects in the analysis and that the Maximum Likelihood estimation faces challenges with a large set of fixed effects, we focus on OLS.

$$CIV(\Delta HC) = \left[1 - \exp\left(\frac{\beta_1}{\beta_2} * \Delta HC\right)\right] * \ y^0 \ \ (3)$$

It is important to note that the parameters β_1 and β_2 are determined by estimating equation (1) using (linear) regression methods. In other words, the CIV provides a metric of the average per cent of a person's income which they are (hypothetically), willing to forego to have access to a healthcare provider. In order to receive the overall absolute value a person is willing to forego, compared to the relative value illustrated in equation (3), one has to multiply equation the content in the large bracket of equation (3) with the average salary y^0.

It is important to highlight that past research suggests that income could exert an effect indirectly on life satisfaction through other variables (Ferrer-i-Carbonell & van Praag 2002). Not accounting for the indirect effect of income on life satisfaction through other variables in the model would result in the coefficient of income being underestimated, the consequence of which would be an overestimation of the value of the non-market good. To account for this issue, we follow a similar approach as Shi et al. (2019) and perform a mediation analysis, which estimates the indirect effect of income through other variables used in the regression model. This is done by removing each variable through which income may have an effect on life satisfaction from the model one at a time. The difference in between the income coefficient obtained from these models and the full model represents the indirect effect of income through that variable on life satisfaction. It is important to highlight that past research suggests that income could exert an effect indirectly on life satisfaction through other variables (Ferrer-i-Carbonell & van Praag 2002).

C.1.2. Data sources and main measures

In order to estimate parameters β_1 and β_2 we use data from the Canadian Community Health Survey (CCHS). The CCHS includes information on a variety of measures such as an individual's physical and mental health, lifestyle, personal attitudes and life satisfaction. The CCHS is a representative large-scale repeated cross-sectional survey of individuals in all of Canada's nine provinces. The CCHS has been used in the past to analyse the monetised value of health behaviours such as physical activity (Shi et al. 2019). In order to estimate the parameters β_1 and β_2 we use the CCHS from the available 2015–2016 and 2017–2018 surveys.

The question on life satisfaction, or the outcome variable LS_{irt}, has been asked in every wave and is based on the question: 'Using a scale of 0 to 10, where 0 means "Very dissatisfied" and 10 means "Very satisfied", how do you feel about your life as a whole right now?'. With regard to the income variable, $\boldsymbol{Inc_{irt}}$, the CCHS only records household income bands instead of the exact income and in line with Frey et al. (2009) and (Layard et al. 2008) we convert these into numerical values using the midpoint of each band. For respondents in the lowest income band we assumed an income of two thirds of the upper limit of the lowest income band, whereas for respondents in the highest income band we assumed an income of 1.5 of the lower income limits of the highest income band. In line with the existing scientific literature (e.g. Howley 2017), we transform the income variable into the equivalent annual household income which is calculated by dividing the total household income by the square root of the household size. This measure implies that a household with for example four members has needs as twice as large as a single household. Following Layard et al. (2008) we exclude the five per cent at either extreme of the income distribution of fitted residuals from a linear regression of log income and a set of standard control variables such as age, gender, education, among others. It is assumed that most of these observations are the result of measurement error or else reflect transitory deviations from usual household income. Including such observations could lead to misleading conclusions about the long-term link between income and individual utility, and Layard et al. (2008) show that there is no clear functional relationship between life satisfaction and the extreme ends of the residual distribution. For the analysis we furthermore only include individuals from Canadian health regions that are considered to be in rural settings, these include the ones in clusters A, C, D, E and F (Statistics Canada 2018b). Overall, our pooled analytic sample across the 13 Canadian provinces includes 102,890 observations.

To measure the perceived barrier to healthcare, we can use two different questions in the CCHS. First, respondents are asked whether they have a regular healthcare provider (PHC_020). About 16 per cent of Canadians report that they do not have a regular healthcare provider. An additional question then asks the reason for not having a regular provider. Among other reasons, such as the provider has recently retired, or there was no need in having one, one answer option is to state that ‘no healthcare provider is available in the area’ (PHC_025B). The lack of supply of healthcare provider in the area is a barrier that could be overcome through the application of TM. Furthermore, both CCHS waves (2015–2016; 2017–2018) used for the analysis also have a special module asking respondents about their unmet healthcare demands. Specifically, the question is ‘During the past 12 months, was there ever a time when you felt that you needed healthcare, other than homecare services, but you did not receive it?’, which is then followed by a follow-up question: ‘Thinking of the most recent time you felt this way, why didn’t you get care? - Care not available in the area’. Unfortunately, the latter question was only optional, and is missing for a large number of respondents in both surveys, e.g. in 2015–2016 the question was only answered for residents in Newfoundland and Labrador, Nova Scotia, Alberta and the Northwest Territories, and in 2017–2018 it was asked only in Nova Scotia, New Brunswick, Ontario, Alberta and Manitoba. This makes any meaningful representative analysis for the whole of Canada problematic. Therefore, our preferred measure is the previous question.

In order to minimise omitted variable bias and with the goal to compare individuals with very similar backgrounds we follow previous studies (e.g. Frey et al. 2009; Howley 2017; Layard et al. 2008) and include the responses from the household member interviewed, including the following control variables that are likely correlated with the outcome variable of subjective well-being and income:

- Age.
- Gender.
- Marital status (e.g. binary variables for being married, common law, widowed/divorced/separated/ or single).
- Current health status.
- Current mental health status.
- Current levels of life stress.
- Educational attainment (less than secondary/secondary/tertiary education).
- Main activity (e.g. working at paid job; vacation from paid job; looking for paid job; caring for children; household work; retired).
- Home ownership.
- Sense of belonging to local community.
- Ethnical background (e.g. white vs others).
- Immigration status (e.g. native; 0-9 years since immigration; 10+ years since immigration).
- Language spoken at home.
- Body Mass Index (e.g. underweight; normal; overweight; obese).
- Smoking status (e.g. non-smoker; daily smoker; occasional smoker).

Table C.2 reports the proportion of sample individuals in rural health regions (about 60 per cent of all respondents) and of the individuals living in rural health regions the share reporting that they have no regular primary care provider as there is not one in their area of living. About 24 per cent of respondents in the Territories report having no primary healthcare provider in their area, compared to about 5.1 per cent in Newfoundland and Labrador, 4.2 per cent in Quebec and 3.6 per cent of Prince Edward Island.

Summary statistics of the variables included in the empirical analysis can be found in Table C.3. Table C.3 compares the characteristics of individuals reporting to have no access to a regular primary healthcare provider versus those that have. The findings suggest that overall, these individuals tend to have lower life satisfaction, and lower levels of equivalent household income. Furthermore, they tend to be between 30 and 54 years old, with lower education levels, less likely homeowners, but more likely in paid work, and less likely in retirement. They also tend to be more likely report to be smokers and feel less likely to be belonging to their community.

Table C.2: Proportion of rural health regions and share of respondents reporting not having a primary care provider, by province

	Health regions rural	Not having local primary care provider
Province	**Per cent**	**Per cent**
Newfoundland and Labrador	100.0	5.1
Prince Edward Island	100.0	3.6
Nova Scotia	68.3	2.6
New Brunswick	100.0	1.7
Quebec	57.9	4.2
Ontario	56.6	1.9
Manitoba	66.1	3.3
Saskatchewan	67.4	3.2
Alberta	47.6	2.6
British Columbia	47.1	3.3
Territories	100.0	23.8
Total	60.3	3.8

%

Table C.3: Descriptive statistics of variables used in the analysis

Variable	Mean	Standard deviation
Life Satisfaction (0: not at all satisfied; 10: fully satisfied)	8.22	1.57
Equivalent household income ($ CAD)	46071.20	18080.52
Age: up to 29	0.22	0.41
Age: between 30 and 54	0.39	0.49
Age: between 55 and 74	0.32	0.47
Age: 75 and older	0.07	0.26
Female (yes/no)	0.49	0.50
Education: less than secondary	0.19	0.40
Education: secondary	0.24	0.43
Education: tertiary	0.57	0.50
Ethnicity: Non-white background	0.04	0.19
Language at home: English	0.68	0.46
Language at home: French	0.27	0.44
Language at home: mix	0.03	0.17
Marital status: married	0.48	0.50
Marital status: common-law	0.16	0.36
Marital status: widowed/divorced/separated	0.12	0.33
Subjective health: poor	0.03	0.16
Subjective health: fair	0.08	0.27
Subjective health: very good	0.38	0.49
Subjective health: excellent	0.23	0.42
Subjective mental health: poor	0.01	0.11
Subjective mental health: fair	0.05	0.22
Subjective mental health: very good	0.37	0.48
Subjective mental health: excellent	0.33	0.47
Life stress: not very stressful	0.26	0.44
Life stress: a bit stressful	0.41	0.49
Life stress: quite a bit stressful	0.17	0.38
Life stress: extremely stressful	0.03	0.16
Home owner	0.81	0.40
Main activity: paid work	0.55	0.50
Main activity: looking for work	0.03	0.16
Main activity: long-term illness	0.02	0.13
Main activity: retired	0.22	0.42
Immigration status: 0-9 years since immigration	0.01	0.11
Immigration status: 10 or more years since immigration	0.05	0.22
BMI: 25-30 (overweight)	0.34	0.47
BMI: > 30 (obese)	0.23	0.42
Current smoker	0.15	0.35
Belonging to community: very weak	0.06	0.24
Belonging to community: very strong	0.19	0.39

Table C.4: Characteristics of individuals reporting not having a regular healthcare provider in the area

Variable	Regular healthcare provider in the area		
	Yes	No	All
Life Satisfaction (0: not at all satisfied; 10: fully satisfied)	8.23	8.01	8.22
Equivalent household income ($ CAD)	46,127.83	44,224.30	46,071.20
Age: up to 29	0.21	0.24	0.22
Age: between 30 and 54	0.39	0.51	0.39
Age: between 55 and 74	0.32	0.22	0.32
Age: 75 and older	0.08	0.03	0.07
Female (yes/no)	0.49	0.42	0.49
Education: less than secondary	0.19	0.19	0.19
Education: secondary	0.24	0.24	0.24
Education: tertiary	0.57	0.57	0.57
Ethnicity: Non-white background	0.04	0.06	0.04
Language at home: English	0.69	0.58	0.68
Language at home: French	0.27	0.35	0.27
Language at home: mix	0.03	0.04	0.03
Marital status: married	0.48	0.34	0.48
Marital status: common-law	0.15	0.26	0.16
Marital status: widowed/divorced/separated	0.12	0.10	0.12
Subjective health: poor	0.03	0.03	0.03
Subjective health: fair	0.08	0.08	0.08
Subjective health: very good	0.38	0.35	0.38
Subjective health: excellent	0.23	0.23	0.23
Subjective mental health: poor	0.01	0.02	0.01
Subjective mental health: fair	0.05	0.07	0.05
Subjective mental health: very good	0.37	0.34	0.37
Subjective mental health: excellent	0.34	0.32	0.33
Life stress: not very stressful	0.26	0.23	0.26
Life stress: a bit stressful	0.41	0.40	0.41
Life stress: quite a bit stressful	0.17	0.21	0.17
Life stress: extremely stressful	0.03	0.05	0.03
Home owner	0.81	0.68	0.81
Main activity: paid work	0.54	0.65	0.55
Main activity: looking for work	0.03	0.04	0.03
Main activity: long-term illness	0.02	0.02	0.02
Main activity: retired	0.23	0.11	0.22
Immigration status: 0-9 years since immigration	0.01	0.02	0.01
Immigration status: 10 or more years since immigration	0.05	0.05	0.05
BMI: 25-30 (overweight)	0.34	0.33	0.34
BMI: > 30 (obese)	0.23	0.23	0.23
Current smoker	0.14	0.24	0.15
Belonging to community: very weak	0.06	0.10	0.06
Belonging to community: very strong	0.19	0.15	0.19

C.2. Empirical results

In this section we present the empirical findings. First, we present the parameter estimates for β_1 and β_2, which are based on estimating equation (1) using the CCHS data. Here, we also test whether the association between the lack of access to a healthcare provider and life satisfaction differs for individuals who live in urban or rural regions. Subsequently, we use the parameter estimates for β_1 and β_2 to build the CIV in each of the provinces to have access to healthcare providers.

C.2.1. Associations between lack of access to a healthcare provider, household income and life satisfaction

Table C.5 reports the parameter estimates from estimating equation (1). The parameter estimate for β_1 in column (1) suggests that, all else being equal, an individual reporting having no healthcare provider in the area, reports on average a lower life satisfaction than an individual that reports to have a regular healthcare provider. As reported in many previous studies, the parameter estimates for β_2 suggests that household income is positively correlated with life satisfaction. Furthermore, we find that life satisfaction tends to be lower in higher ages compared to individuals with age up to 29. We also find that women tend to report a higher life satisfaction. Compared to singles (the baseline category for marital status), we also find that couples that are married or are common in law are happier but those widowed, divorced or separated are reporting lower levels of life satisfaction.

Table C.5: Associations between lack of access to healthcare provider, equivalent income and life satisfaction; using data from the CCHS (2015–2018) for 9 provinces

	(1)	(2)
Variables	**Coefficient**	**Standard error**
Equivalent household income (β_2)	0.0810	(0.0116)*
No regular primary care provider in the area (β_1)	-0.0469	(0.0234)*
Age (base category age below 30)		
Age: between 30 and 54	-0.1806	(0.0140)*
Age: between 55 and 74	-0.2306	(0.0185)*
Age: 75 and older	-0.2194	(0.0219)*
Female (yes/no)	0.1614	(0.0078)*
Education (base category tertiary degree)		
Education: less than secondary	0.1270	(0.0134)*
Education: secondary	-0.0004	(0.0095)
Ethnicity: Non-white background	-0.1168	(0.0289)*
Language spoken at home (base category English)		
Language at home: French	-0.0263	(0.0191)
Language at home: mix	0.0746	(0.0210)*
Language at home: other	-0.0624	(0.0505)
Marital status (base category single)		
Marital status: married	0.3469	(0.0126)*
Marital status: common-law	0.2882	(0.0155)*
Marital status: widowed/divorced/separated	-0.0487	(0.0164)*
Subjective health (base category 'good')		

	(1)	(2)
Variables	**Coefficient**	**Standard error**
Subjective health: poor	-1.4777	(0.0487)*
Subjective health: fair	-0.5751	(0.0225)*
Subjective health: very good	0.3102	(0.0099)*
Subjective health: excellent	0.6243	(0.0128)*
Subjective mental health (base category 'good')		
Subjective mental health: poor	-1.7504	(0.0535)*
Subjective mental health: fair	-0.7067	(0.0269)*
Subjective mental health: very good	0.4269	(0.0149)*
Subjective mental health: excellent	0.7945	(0.0151)*
Life stress (base category not stressful)		
Life stress: not very stressful	-0.2904	(0.0125)*
Life stress: a bit stressful	-0.5407	(0.0165)*
Life stress: quite a bit stressful	-0.8777	(0.0270)*
Life stress: extremely stressful	-1.3057	(0.0527)*
Home owner (base category rent)	0.0901	(0.0147)*
Main activity (base category 'other')		
Main activity: paid work	0.0245	(0.0141)
Main activity: looking for work	-0.4029	(0.0341)*
Main activity: long-term illness	-0.4839	(0.0476)*
Main activity: retired	-0.0882	(0.0152)*
Immigration status (base category no immigrant status)		
Immigration status: 0-9 years since immigration	-0.1168	(0.0409)*
Immigration status: 10 or more years since immigration	-0.0398	(0.0217)
Body Mass Index (base category BMI below 25)		
BMI: 25-30 (overweight)	0.0465	(0.0104)*
BMI: > 30 (obese)	0.0643	(0.0150)*
Smoking status (base category non-smoker)		
Current smoker	-0.1059	(0.0127)*
Belonging to community (base category feels ok)		
Belonging to community: very weak	-0.3678	(0.0322)*
Belonging to community: very strong	0.3252	(0.0108)*
Observations	102,927	
R-squared	0.404	

*Notes: Clustered standard errors (health region) in parentheses; * p<0.05. Regression model additionally adjusted for health region and year fixed effects.*

Not surprisingly, we find a positive association between good general and mental health and life satisfaction, as well as for perceived levels of life stress, with lower levels of stress associated with better levels of life satisfaction. We further find that immigrants that have been living in Canada for less than 9 years report lower life satisfaction, as well as smokers. We do find a positive correlation between higher levels of BMI and life satisfaction but a negative association between reporting not belonging to the community.

Table C.6 presents the results of the mediation analysis, demonstrating the indirect effects of income through other variables on life satisfaction. We find that income has a positive effect on life satisfaction through home ownership, health status, mental health and main activity, as well as a negative effect through marital status. Variables such as age, gender were not removed from the mediation analysis as income cannot change age, gender. The cumulative effect of dropping each of these variables was an increase in the income coefficient by 0.162, which represents the aggregated indirect effect of income on life satisfaction. The total income effect is calculated by using the direct effect from the full model (0.081) added to the indirect effect resulting in a total income effect of 0.243, which is the value for β_2 that can be used for the individual CIV calculation using equation (3).

Table C.6: Indirect effects of income through other variables on life satisfaction

	Income coefficient	Change in income coefficient
Full model (Direct effect)	**0.081**	
Variable dropped		
Marital status	0.080	-0.001
Home ownership	0.098	0.017
Main activity	0.135	0.054
Health status	0.131	0.050
Mental health status	0.122	0.041
Total indirect effect		0.162
Total income effect (β_2)	0.243	

C.2.2. Estimating the individual compensating variation for not having access to a healthcare provider

Using the parameter estimates for β_1 and β_2 from Tables C.5 (column 1) and C.6 (total income effect) one can estimate the compensating income variation for not having access to a healthcare provider, or in other words, the income that an individual would need to be compensated to achieve the same level of life satisfaction that is foregone because it has not a regular primary healthcare provider.

The estimation of the β_2 coefficient of income in the regression model is critical as all monetary values derived in relation with it will have to be based on the full causal effect of income on life satisfaction. Calculating the causal effect for income is challenging because other variables that drive life satisfaction may also correlate with income within the model. Controlling for variables that partially rely on income to have effects on life satisfaction removes these effects from the full effect of income, resulting in smaller coefficients for the income variable and potentially then overestimates the monetary values of the nonmarket goods estimated through the application of equation (3). We have aimed to account for the indirect effects of income using the mediation analysis. Recent economic studies have attempted to account for the indirect effect of income using mediation analysis, resulting in a larger coefficient for β_2. Although our study has controlled for as many of the determinants of life satisfaction as possible in our regression models, our inability to include all variables related to life satisfaction prevents the full causal effect of income from being fully accounted for with the approach. To further deal with the issue of causality and the full effect of income in these type of models, recent economic studies have attempted to use an instrumental variable (IV) approach, which eliminates the correlation between the income variable and the error term of the model depicted in equation (1). Existing studies use for instance parental education as an IV for an individual's income (Howley 2017); proxy measures for the intelligence of an individual (e.g. interviewer information on how well the person understood the questions, independent of language spoken (Brown 2015) or using lottery wins (Fujiwara et al. 2014), such as a study commissioned by the United Kingdom government which estimated the well-being impact of culture and sport. In that study, the coefficient of income on life satisfaction using the IV approach was estimated to be 1.16, which is about 4.8 times larger than our estimate. Unfortunately, with the CCHS data, we do not have a suitable IV at hand, but we use our income coefficient of 0.243 to calculate the upper bound value of the CIV and the coefficient 1.16 to calculate the lower bound value of the CIV.

Table C.7 reports the compensating income variations by province and for Canada as a whole. We estimate that the extra equivalent household income required to leave an individual with no primary healthcare provider in the area of living as well-off in life-satisfaction terms as someone with access to a primary healthcare provider amounts to between CAD 1,901 and CAD 9,817 per annum. To put this into perspective, it has been estimated that the annual cost for public health insurance costs a single individual CAD 4,894 per annum (e.g. calculated through the tax contributions) (Palacios & Barua 2020).

Table C.7: Compensating income variations by province

Province	Equivalent income (per annum)	CIV: low (per annum)	CIV: high (per annum)
Newfoundland and Labrador	44,262	-1,826	-9,431
Prince Edward Island	43,240	-1,784	-9,214
Nova Scotia	42,371	-1,748	-9,028
New Brunswick	45,098	-1,861	-9,610
Quebec	43,907	-1,812	-9,356
Ontario	46,985	-1,939	-10,012
Manitoba	45,468	-1,876	-9,688
Saskatchewan	47,063	-1,942	-10,028
Alberta	50,216	-2,072	-10,700
British Columbia	47,708	-1,968	-10,166
Territories	47,784	-1,972	-10,182
Canada	46,071	-1,901	-9,817

Notes: values in (2019) Canadian Dollars.

Furthermore, Table C.8 compares the CIV for no regular primary healthcare provider available with other factors that are associated with life satisfaction in our analysis.

Table C.8: Compensating income variation comparison

	CIV (per annum)
No regular primary care provider available	-1,901
Married	11,908
Home owner	3,443
Life stress: a bit stressful	-27,357

Notes: Uses parameter coefficient for each variable as reported in Table A.5 and 1.16 as income coefficient.

For example, we find that the amount of income needed to compensate someone who is married to leave them as well-off in life-satisfaction terms as someone is single amounts to CAD 11,908 per annum. The amount needed to compensate someone who is a homeowner to leave them as well-off in life-satisfaction terms as someone who does not own a home is CAD 3,443 per annum. Finally, we estimate that the individual compensating variation for an individual feeling stressed is relatively large, where an individual feeling a bit stressful would need to be compensated by CAD 27,357 per annum to have same life satisfaction as a person that is not felling stressed at all.

C.2.3. Estimating the aggregated welfare loss for not having a primary healthcare provider available

In Table C.7 we have monetised the average utility or welfare loss for each individual in Canada that currently reports not having a primary care provider in the area available, suggesting a local mismatch between supply and demand of healthcare. In this section we assume that a fraction of these individuals could be served through TM and potentially link them with a healthcare provider that may not be in the area through online consultations, and then aggregate the individual potential welfare gains from this for each of the Canadian provinces.

For that reason, we multiply the total number of individuals in rural health regions that report not having a health provider available and multiply that with the average individual CIV. Note that we use the lower bound estimate of CIV to estimate the aggregated potential welfare gains. We follow a scenario structure where we assume that (1) 5 per cent; (2) 10 per cent; (3) 25 per cent; or (4) 50 per cent of those not having access to a primary care provider could be sorted out through remote consultations. The corresponding findings are reported in Table C.9.

We find that, depending on the scenario on how many people would use TM as a substitute for in-person consultations with a primary healthcare provider, a potential aggregated welfare gain between CAD 61m (5 per cent) to CAD 611m (50 per cent) could be achieved across Canada.

Table C.9: Estimated total welfare gains of providing access to healthcare provider through TM by province

	TM scenario (CAD, per annum)			
	5 per cent	10 per cent	25 per cent	50 per cent
Newfoundland and Labrador	2,437,461	4,874,923	12,187,306	24,374,613
Prince Edward Island	505,000	1,009,999	2,524,999	5,049,997
Nova Scotia	1,505,095	3,010,190	7,525,475	15,050,951
New Brunswick	1,228,889	2,457,777	6,144,443	12,288,886
Quebec	18,731,044	37,462,088	93,655,219	187,310,439
Ontario	15,164,327	30,328,655	75,821,637	151,643,274
Manitoba	2,802,160	5,604,320	14,010,801	28,021,602
Saskatchewan	2,455,097	4,910,193	12,275,484	24,550,967
Alberta	5,592,362	11,184,723	27,961,808	55,923,617
British Columbia	7,786,265	15,572,531	38,931,327	77,862,654
Territories	2,936,143	5,872,285	14,680,713	29,361,425
Canada	61,143,843	122,287,685	305,719,213	611,438,425