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The impact of pharmaceutical innovation on mortality and hospital utilization in Canada, 2000–2022

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ABSTRACT

A previous study found that Canadian mortality and hospital utilization were reduced during the period 2000-2016 by new drug authorizations many years earlier. Since 2016, there have been substantial changes in premature mortality and average length of hospital stays in Canada. This study reexamines the impact that pharmaceutical innovation had on mortality and hospital utilization in Canada during the period 2000–2022. In addition to analyzing a longer and more recent sample period, this study builds upon the previous analysis in several important respects. The estimates imply that, in the absence of drug approvals during 1974-1995, the number of life-years lost before age 75 (YLL75) would have been 49% higher in 2022. Drug approvals during 1974-1995 reduced YLL75 in 2022 by 847 thousand. The authorization of new classes of drugs has a more immediate effect on mortality than the authorization of new drugs, but the former effect is smaller and less statistically significant than the latter effect. For example, new classes of drugs authorized during 1990-2011 are estimated to have reduced the growth in the number of years of life lost before age 65 during 2000-2022 by 29%, whereas new drugs authorized during 1978-1999 are estimated to have reduced the growth in the number of years of life lost before age 65 during 2000-2022 by 39%. This may signify that mortality is more strongly related to the importance-weighted number of classes than it is to the unweighted number of classes, and that the more important or significant a class is, the larger the number of substances that were launched in the class. The estimates also imply that, in the absence of drug approvals during 1970-1991, the total number of hospital days (DAYS) would have been 55% higher in 2022. Drug approvals during 1970-1991 reduced DAYS in 2022 by 14.2 million. The estimated reduction in 2022 hospital expenditure attributable to drug approvals during 1970-1991 is about twice as large as 2022 expenditure on all prescribed medicines (CA$ 37.4 billion). These estimates may be conservative, because the models do not fully capture the health impacts of COVID-19 vaccines. A previous study argued that those vaccines reduced the number of COVID-19 cases by 21%, the number of COVID-19 hospitalizations by 37%, and the number of COVID-19 deaths by 63%. In addition to analyzing the relationship between pharmaceutical innovation and mortality using national data, this study examined the relationship between access to drugs covered in public drug program formularies and mortality using data by province, disease, and year. The age-adjusted mortality rate from a given disease in a given province in a given year is significantly inversely related to the number of drugs that are used to treat that disease and that were covered in public drug program formularies in that province 4-12 years earlier, controlling for the average (across years) level of mortality and drug access of each disease in each province, the average (across provinces) level of mortality and drug access of each disease in each year, and the average (across diseases) level of mortality and drug access of each province in each year.

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INTRODUCTION

An earlier study (Lichtenberg (2019)) analyzed the impact that pharmaceutical innovation—the introduction and use of new drugs—had on the burden of disease in Canada during the period 2000–2016. The estimates in that study showed that new drug launches during 1986–2001 reduced the number of years of life lost in 2016 by 28%, and that, if no drugs had been launched during 1986–2001, the average length of 2016 hospital stays would have been about 16% higher.

After 2016, there were substantial changes in premature mortality and average length of hospital stays in Canada. The data in Figure 1A indicate that, from 2016 to 2022, the Canadian premature (before age 75) mortality rate increased by 12%; from 2000 to 2016, it had declined by 20%. The data in Figure 1B indicate that, from 2016 to 2022, the average length of hospital stays increased at an average annual rate of 1.1%; from 2000 to 2016, it had increased at an average annual rate of 0.3%.

This study analyzed the impact that pharmaceutical innovation had on mortality and hospital utilization in Canada during the period 2000–2022. Like the previous study, the analysis used a difference-in-differences (or two-way fixed effects) research design to investigate whether diseases for which more new drugs were launched had larger subsequent declines (or smaller increases) in mortality and hospital utilization. This design controls for the effects of general economic and societal factors (e.g. income, education, and behavioral risk factors), to the extent that those effects are similar across diseases, e.g. smoking increases mortality from respiratory and cardiovascular disease as well as lung cancer, and education reduces mortality from all diseases.

However, in addition to analyzing a longer and more recent sample period, the analysis in this study differs from, and builds upon, the previous analysis in several important respects:

- The previous study analyzed a single measure of disease-specific mortality: years of life lost, as defined in the WHO Global Burden of Disease Project. The present study analyzed four measures of disease-specific mortality: the number of deaths, and the number of years of life lost before ages 85, 75, and 65.

- The previous study analyzed just two years—2000 and 2016—of mortality and hospital utilization data, i.e. it analyzed just the long-run changes in those variables. The present study analyzed annual data for all 23 years of the period 2000-2022.

- This study used a different classification of diseases by cause of death: the 113 ICD-10 Cause of Death Recode used in the U.S. Centers for Disease Control and Prevention National Death Index.[1]

- In addition to investigating whether diseases for which more new *drugs* were launched had larger subsequent declines in mortality and hospital utilization, this study investigated whether diseases for which more *drug classes* were launched had larger subsequent declines in mortality and hospital utilization.

- The study also analyzed the impact of geographical (across provinces) variation in access to drugs covered in public drug program formularies on age-adjusted mortality rates.

[1] This disease classification does not separately identify COVID-19. This study augmented the classification to include COVID-19 (ICD10 U07).

METHODS

Mortality: national level

To assess the impact that pharmaceutical innovation had on mortality during the period 2000-2022, the following 2-way fixed effects equation was estimated:

$$\ln(Y_{dt}) = \beta_k \ln(CUM\_DRUG_{d,t-k}) + \alpha_d + \delta_t + \varepsilon_{dt} \qquad (1)$$

where Y_{dt} is one of the following variables:

N_DEATHS_{dt} = the number of deaths caused by disease d in year t (t = 2000, 2001, …, 2022)

$YLL85_{dt}$ = the number of years of life lost before age 85 from disease d in year t

$YLL75_{dt}$ = the number of years of life lost before age 75 from disease d in year t

$YLL65_{dt}$ = the number of years of life lost before age 65 from disease d in year t

and

$CUM\_DRUG_{d,t-k}$ = $\sum_m INDIC_{md}\, LAUNCHED_{m,t-k}$ = the number of (5th-level, WHO ATC) chemical *substances* to treat disease d that had been launched in Canada by the end of year t-k (k = 0, 2, 4, …, 30)

$INDIC_{md}$ = 1 if chemical substance m is used to treat (indicated for) disease d [2]

= 0 if chemical substance m is not used to treat (indicated for) disease d

$LAUNCHED_{m,t-k}$ = 1 if chemical substance m had been launched in Canada by the end of year t-k

= 0 if chemical substance m had not been launched in Canada by the end of year t-k

α_d = a fixed effect for disease d

δ_t = a fixed effect for year t

To address the issue of heteroskedasticity, eq. (1) was estimated by weighted least squares, weighting by $\sum Y_{dt}$. Disturbances were clustered within diseases. Eq. (1), which may be considered a "health production function", has a logarithmic specification, which is standard in the production function literature. Unlike a linear production function, this specification is robust to changes in the level of disease classification. Since the logarithm of zero is not defined, observations where either $Y_{dt} = 0$ or $CUM\_DRUG_{d,t-k} = 0$ are excluded. The first deaths from COVID-19 occurred and the first COVID-19 vaccines were approved in 2020.[3] Consequently, the set of diseases upon which estimates of eq. (1) are based will not include COVID-19 when t < 2020, when t = 2020 and k > 0, or when t = 2022 and k > 2. To test the robustness of the estimates, eq. (1) was estimated in two ways: excluding and including COVID-19 observations. In eq. (1), mortality is allowed to depend on the number of chemical substances that had been launched up to 30 years earlier.

[2] Many drugs have multiple indications: 50% of drugs have 2 or more indications (causes of disease in the WHO Global Health Estimates disease classification), and 7% of drugs have 5 or more indications.

[3] The number of deaths from COVID-19 in 2020, 2021, and 2022, were 16313, 14463, and 19709, respectively. COVID-19 accounted for 5.3% = (50,485 / 954,133) of deaths during 2020-2022 and for 0.9% = (50,485 / 5,857,696) of deaths during 2000-2022. The first COVID-19 vaccines approved were: J07BN01 (COVID-19, RNA-based vaccine), approved 12/9/2020; J07BN02 (COVID-19, viral vector, non-replicating), approved 2/26/2021; and J07BN04 (COVID-19, protein subunit), approved 2/17/2022.

Lichtenberg (2019) showed that utilization of a drug reaches a peak about 12-14 years after it was launched; see Figure 2. It is used about twice as much then as it was 4 years after launch. Due to gradual diffusion of new drugs, the maximum impact of a drug on mortality is likely to occur many years after it was launched, but the peak effect could occur either more than or less than 12-14 years after launch. The lag might be longer because some drugs for chronic diseases (e.g. statins) may have to be consumed for several years to achieve full effectiveness.[4] But the lag might be shorter because the impact of a drug on disease burden is likely to depend on its quality (or effectiveness) as well as on its quantity (utilization), and drugs launched more recently are likely to be of higher quality than earlier-vintage drugs. [5, 6]

In addition to estimating eq. (1), the following model was estimated:

$$\ln(Y_{dt}) = \pi_k \ln(CUM\_CLASS_{d,t-k}) + \alpha_d + \delta_t + \varepsilon_{dt} \qquad (2)$$

where:

$CUM\_CLASS_{d,t-k}$ = the number of (4th-level WHO ATC) chemical *subgroups* to treat disease d that had been launched in Canada by the end of year t-k.

If most or all substances within a subgroup are essentially equivalent, mortality may depend more on the number of subgroups than it does on the number of substances. However, it is possible that the more important or significant a subgroup is, the larger the number of substances that tend to be launched in the subgroup. Mortality may be more strongly related to the importance-weighted number of subgroups than it is to the unweighted number of subgroups. In that case, mortality would depend more on the number of substances than it does on the number of subgroups.

Estimates of eqs. (1) and (2) will not capture cross-disease spillover effects: the potential effects of pharmaceutical innovation for one disease (e.g., hypertension) on mortality from other diseases (e.g., acute cerebrovascular disease (stroke)). Although some spillover effects are adverse, others—perhaps most—are positive. For example, Prince et al (2007) argued that "mental disorders increase risk for communicable and non-communicable diseases and contribute to unintentional and intentional injury. Conversely, many health conditions increase the risk for mental disorder, and comorbidity complicates help-seeking, diagnosis, and treatment, and influences prognosis." Also, the NIH National Institute on Aging (2024) says that "conditions such as diabetes, depression, and stroke may increase a person's risk for Mild Cognitive Impairment." A large clinical trial found that the death rate from *all causes* was lower among subjects taking an obesity drug (Kolata (2024)).

Mortality: provincial level

In addition to analyzing the relationship between pharmaceutical innovation and mortality using national data, the study examined the relationship between access to drugs covered in public drug program formularies and mortality using data by province, disease, and year using the following 3-way fixed-effects model:

$$\ln(AA\_MORT_{dpt}) = \rho_k \ln(N\_DRUG_{dp,t-k}) + \alpha_{dp} + \delta_{dt} + \phi_{pt} + \varepsilon_{dpt} \qquad (3)$$

[4] Improvement in outcomes may occur several years after changes in treatment (van de Glind et al (2016), Barter and Waters (2018)).

[5] Grossman and Helpman (1993) argued that "innovative goods are better than older products simply because they provide more 'product services' in relation to their cost of production." Bresnahan and Gordon (1996) stated simply that "new goods are at the heart of economic progress," and Bils (2004) said that "much of economic growth occurs through growth in quality as new models of consumer goods replace older, sometimes inferior, models." As noted by Jovanovic and Yatsenko (2012), in "the Spence–Dixit–Stiglitz tradition…new goods [are] of higher quality than old goods."

[6] The impact on mortality may depend on the *interaction* (quantity * quality) of the two variables. The mortality impact will increase with respect to drug age (time since launch) if the rate of increase of quantity with respect to age is greater than the rate of decline of quality with respect to age; otherwise the mortality impact will decline.

where:

AA_MORT_{dpt} = the age-standardized mortality rate from disease (leading cause of death) d in province p in year t

$N\_DRUG_{dp,t-k}$ = the number of (5^{th}-level, WHO ATC) chemical substances used to treat disease d that were covered by at least one public formulary in province p in year t-k (k = 0, 2, 4, …, 18)

α_{dp} = a fixed effect for disease d in province p

δ_{dt} = a fixed effect for disease d in year t

ϕ_{pt} = a fixed effect for province p in year t

The fixed effects control for the average level of mortality and drug access of each disease in each province, the average level of mortality and drug access of each disease in each year, and the average level of mortality and drug access of each province in each year. Eq. (3) was estimated by weighted least-squares, weighting by N_DEATHS_{dpt} = the number of deaths in province p caused by disease d in province p in year t. Disturbances were clustered by disease and province. The disease classification used for the eq. (3) data is shown in Appendix Table 1.

As shown in Appendix Table 2, the time coverage of the formulary data varies across provinces. Data for four provinces are available from at least 1995. Data for six other provinces start to become available at some point during 2000-2004. The data for Quebec appear to be quite incomplete. Eq. (3) was estimated both excluding and including data for Quebec.

Hospital utilization: national level

To assess the impact that pharmaceutical innovation had hospital utilization during the period 2000-2022, the following 2-way fixed effects equation was used:

$$\ln(Y_{dt}) = \beta_k \ln(CUM\_DRUG_{d,t-k}) + \alpha_d + \delta_t + \varepsilon_{dt} \qquad (4)$$

where Y_{dt} is one of the following variables:

$DISCHARGES_{dt}$ = the number of hospital discharges caused by disease d in year t (t = 2000, 2001, …, 2022)

$ALOS_{dt}$ = the average length of hospital stays for disease d in year t

$DAYS_{dt}$ = the number of hospital days (= $DISCHARGES_{dt}$ * $ALOS_{dt}$) for disease d in year t

Eq. (4) will be estimated by weighted least squares. When $Y_{dt} = DISCHARGES_{dt}$, the weight will $\sum_t DISCHARGES_{dt}$. When $Y_{dt} = ALOS_{dt}$, the weight will be $DISCHARGES_{dt}$. When $Y_{dt} = DAYS_{dt}$, the weight will be $\sum_t DAYS_{dt}$. Disturbances will be clustered within diseases.

DATA SOURCES

National mortality data. Data on N_DEATHS_{dt}, $YLL85_{dt}$, $YLL75_{dt}$, and $YLL65_{dt}$ were constructed from data contained in the WHO Mortality Database.

Drug launch data. Health Canada's Drug Products Database (Health Canada (2024)) was used to determine the years in which (WHO ATC 5^{th}-level) chemical substances first received market authorization in Canada. The rate of increase in the number of substances ever approved has declined. During the 1960s and 1970s, the number of substances ever approved increased at an average annual rate of 4.5%. During the 1980s and 1990s, it increased at an average annual rate of 3.7%. From 2000 to 2020, it increased at an average annual rate of 1.8%.

Drug indications data. Indications (coded by ICD-10) of chemical substances were obtained from Theriaque, a database produced by the French Centre National Hospitalier d'Information sur le Médicament (2024).[7]

Provincial mortality data. Data on AA_MORT$_{dpt}$ and N_DEATHS$_{dpt}$ were obtained from Statistics Canada Table 13-10-0801-01 Leading causes of death, total population (age standardization using 2011 population).

Provincial drug data. Data on drugs covered in public drug program formularies (N_DRUG$_{dp,t-k}$) were constructed from Canadian Institute for Health Information Formulary coverage.

Hospitalization data. Data on the number of hospital discharges and average length of stay, by diagnosis, were obtained from the OECD Data Explorer (OECD (2024a)). The disease classification scheme is provided in OECD's International shortlist for hospital morbidity tabulation (OECD (2024b)).

EMPIRICAL RESULTS

Mortality: national level

Estimates of β_k from eq. (1) are shown in Table 1 and plotted in Figure 3.[8] Each estimate is from a separate regression. In the table, estimates in bold are statistically significant (p-value < .05), and "trend" and "effect" are defined as follows:

$$\text{trend}_k = \text{weighted\_mean}[\ln(\text{CUM\_DRUG}_{d,2022-k}/\ \text{CUM\_DRUG}_{d,2000-k})]$$

$$\text{effect}_k = \beta_k * \text{trend}_k$$

In the figure, hollow squares denote insignificant estimates, solid squares denote statistically significant estimates, and the largest solid squares indicate the most significant estimates. Panel A in Table 1 and Figure 3 shows the estimates when the dependent variable is N_DEATHS$_{dt}$. When $k \leq 6$ (and when $k = 10$), the estimates are not statistically significant. However, when $k \geq 12$ (and when $k = 8$), the estimates are negative and significant. The number of deaths from a disease is not significantly related to the number of drugs that had been authorized to treat the disease up until 6 years before, but is significantly inversely related to the number of drugs that had been authorized to treat the disease up until 12-30 years before. It is most strongly inversely related to the number of drugs that had been authorized to treat the disease up until 28 years before. The magnitude of the β_k estimate (the elasticity of the number of deaths to the number of drugs that had previously been authorized) is largest when $k = 20$. The existence of a substantial lag is not surprising: as discussed above, peak utilization of a drug occurs many years after it was first authorized, and some drugs must be consumed for several years to achieve full effectiveness. The magnitude of effect$_k$ (= β_k * trend$_k$) is largest when $k = 22$. This implies that the drugs authorized during 1978-1999 reduced the growth in the number of deaths during 2000-2022 by 47% (= 1 – exp(-0.636)).

Panel B in Table 1 and Figure 3 shows the estimates when the dependent variable is YLL85$_{dt}$. The estimates are qualitatively similar to the estimates in Panel A. The number of years of life lost before age 85 from a disease is significantly inversely related to the number of drugs that had been authorized to treat the disease up until 8-30 years before. Once again, the magnitude of effect$_k$ (= β_k * trend$_k$) is largest when $k = 22$. This implies that the drugs authorized during 1978-1999 reduced the growth in the number of years of life lost before age 85 during 2000-2022 by 37% (= 1 – exp(-0.468)). Panels C and D in Table 1 and Figure 3 show the estimates when the dependent variables are YLL75$_{dt}$ and YLL65$_{dt}$, respectively. The estimates are similar to the estimates in Panel B. The numbers of years of life lost before ages 75 and 65 from a disease are significantly inversely related to the number of drugs that had been authorized to treat the disease up until 12-28 years before.

Estimates of π_k from eq. (2), in which ln(CUM_DRUG$_{d,t-k}$) is replaced by ln(CUM_CLASS$_{d,t-k}$), are shown in Table 2 and plotted in Figure 4. Panel A in Table 2 and Figure 4 shows the estimates of π_k from eq. (2) when the dependent variable is N_DEATHS$_{dt}$. The estimates of π_k are significant only when $k = 6$ and $k = 8$. Panel B in Table 2 and

[7] Theriaque provides data only on labeled indications; it does not provide data on off-label indications.
[8] The set of diseases upon which the estimates shown in Table 1 and plotted in Figure 3 are based does not include COVID-19. Excluding COVID-19 has virtually no effect on the estimates.

Figure 4 shows the estimates of π_k from eq. (2) when the dependent variable is $YLL85_{dt}$. The estimates of π_k are significant when $2 \leq k \leq 10$. When the dependent variable is $YLL75_{dt}$ (Panel C), the estimates of π_k are significant when $0 \leq k \leq 10$, and when the dependent variable is $YLL65_{dt}$ (Panel D), the estimates of π_k are significant when $0 \leq k \leq 12$. Evidently, the authorization of new *classes* of drugs has a more immediate effect on mortality than the authorization of new drugs, but the former effect is smaller and less statistically significant than the latter effect. For example, new *classes* of drugs authorized during 1990-2011 are estimated to have reduced the growth in the number years of life lost before age 65 during 2000-2022 by 29% (= 1 – exp(-0.337)), whereas new *drugs* authorized during 1978-1999 are estimated to have reduced the growth in the number years of life lost before age 65 during 2000-2022 by 39% (= 1 – exp(-0.496)). This may signify that mortality is more strongly related to the importance-weighted number of subgroups than it is to the unweighted number of subgroups, and that the more important or significant a subgroup is, the larger the number of substances that were launched in the subgroup.

Mortality: provincial level

Estimates of ρ_k from eq. (3) are shown in Table 3 and plotted in Figure 5. Panel A in the table and figure shows estimates of ρ_k based on data on all Canadian provinces (including Quebec, whose data appear to be quite incomplete). The estimates of ρ_k are negative and statistically significant when k equals 4, 10 and 12. Panel B in the table and figure shows estimates of ρ_k when Quebec is excluded. In this case, the estimates of ρ_k are negative and statistically significant when $4 \leq k \leq 12$: the age-adjusted mortality rate from a given disease in a given province in a given year is significantly inversely related to the number of drugs that are used to treat that disease and that were covered in public drug program formularies in that province 4-12 years earlier, controlling for the average (across years) level of mortality and drug access of each disease in each province, the average (across provinces) level of mortality and drug access of each disease in each year, and the average (across diseases) level of mortality and drug access of each province in each year.

Hospital utilization: national level

Estimates of β_k from eq. (1) are shown in Table 4 and plotted in Figure 6. Panel A in Table 4 and Figure 6 shows the estimates when the dependent variable is $DISCHARGES_{dt}$. None of the estimates of β_k are statistically significant.[9] Panel B shows the estimates when the dependent variable is $ALOS_{dt}$. The estimates of β_k are negative and significant when $18 \leq k \leq 28$ (and also when $k = 0$): average length of stay for a disease is significantly inversely related to the number of drugs that had been authorized to treat the disease up until 18-28 years before. Panel C shows the estimates when the dependent variable is $DAYS_{dt}$. The estimates of β_k are negative and significant when $0 \leq k \leq 4$ and also when $18 \leq k \leq 30$: the total number of hospital days for a disease is significantly inversely related to the number of drugs that had been authorized to treat the disease up until 18-30 years before.

DISCUSSION

Estimates of eq. (1) and of another, simpler equation allowed comparison with the counterfactual 2000-2022 trajectory of mortality or hospital utilization, in the absence of previous drug authorizations, to the actual trajectory, in the presence of those authorizations. The year fixed effects (δ_t's) of eq. (1) indicate the (counterfactual) 2000-2022 trajectory of the dependent variable, *holding constant* $CUM\_DRUG_{d,t-k}$, i.e., in the *absence* of pharmaceutical innovation. For example, the weighted mean growth during 2000-2022 of YLL75 in the absence of drug approvals during 1974-1995 is indicated by the year fixed effects (δ_t's) of the equation[10]

$$\ln(YLL75_{dt}) = \beta_{26} \ln(CUM\_DRUG_{d,t-26}) + \alpha_d + \delta_t + \varepsilon_{dt} \qquad (5)$$

The weighted mean growth during 2000-2022 of YLL75 in the *presence* of drug approvals during 1974-1995 is indicated by the year fixed effects (ϕ_t's) of the equation

[9] Lichtenberg (2019) also found that the effect of $CUM\_DRUG_{d,t-k}$ on $DISCHARGES_{dt}$ was insignificant during the period 2000–2016.

[10] As shown in Panel C of Table 1 and Figure 3, when $Y_{dt} = YLL75_{dt}$, the value of k for which β_k is most significant is k = 26: β_{26} = -0.355 (Z = 2.79).

$$\ln(YLL75_{dt}) = \alpha_d + \phi_t + \varepsilon_{dt} \qquad (6)$$

The estimated aggregate 2000-2022 values of YLL75 in the presence and absence of drug approvals during 1974-1995 are shown in Panel A of Figure 7. The actual value of YLL75 increased from 1499 thousand in 2000 to 1718 thousand in 2022. Our estimates imply that, in the absence of drug approvals during 1974-1995, YLL75 would have increased from 1499 thousand in 2000 to 2565 thousand in 2022: YLL75 would have been 49% higher in 2022. Drug approvals during 1974-1995 reduced YLL75 in 2022 by 847 thousand.

Panel B of Figure 7 compares the actual evolution of the number of hospital days to the counterfactual evolution, in the absence of drug approvals during 1970-1991.[11] The actual number of hospital days increased from 20.8 million in 2000 to 25.9 million in 2022. Our estimates imply that, in the absence of drug approvals during 1970-1991, DAYS would have increased from 20.8 million in 2000 to 40.1 million in 2022: DAYS would have been 55% higher in 2022. Drug approvals during 1970-1991 reduced DAYS in 2022 by 14.2 million.

It is reasonable to suppose that, in the absence of drug approvals during 1970-1991, hospital expenditure would also have been 55% higher in 2022. According to the OECD, 2022 expenditure on hospital (curative and rehabilitative) care was CA$ 143.0 billion. This implies that, in the absence of drug approvals during 1970-1991, hospital expenditure would have been CA$ 78.7 billion (= 55% * CA$ 143.0 billion) higher. The estimated reduction in 2022 hospital expenditure attributable to drug approvals during 1970-1991 is about twice as large as 2022 expenditure on all prescribed medicines (CA$ 37.4 billion).

SUMMARY

A previous study found that Canadian mortality and hospital utilization were reduced during the period 2000-2016 by new drug authorizations many years earlier. Since 2016, there have been substantial changes in premature mortality and average length of hospital stays in Canada. This study reexamines the impact that pharmaceutical innovation had on mortality and hospital utilization in Canada during the period 2000–2022. In addition to analyzing a longer and more recent sample period, this study builds upon the previous analysis in several important respects.

The estimates imply that, in the absence of drug approvals during 1974-1995, the number of life-years lost before age 75 (YLL75) would have been 49% higher in 2022. Drug approvals during 1974-1995 reduced YLL75 in 2022 by 847 thousand.

The authorization of new *classes* of drugs has a more immediate effect on mortality than the authorization of new drugs, but the former effect is smaller and less statistically significant than the latter effect. For example, new *classes* of drugs authorized during 1990-2011 are estimated to have reduced the growth in the number of years of life lost before age 65 during 2000-2022 by 29%, whereas new *drugs* authorized during 1978-1999 are estimated to have reduced the growth in the number of years of life lost before age 65 during 2000-2022 by 39%.

The estimates also imply that, in the absence of drug approvals during 1970-1991, the total number of hospital days (DAYS) would have been 55% higher in 2022. Drug approvals during 1970-1991 reduced DAYS in 2022 by 14.2 million. The estimated reduction in 2022 hospital expenditure attributable to drug approvals during 1970-1991 is about twice as large as 2022 expenditure on all prescribed medicines (CA$ 37.4 billion).

These estimates may be conservative, because the models do not fully capture the health impacts of COVID-19 vaccines. Wyonch and Zhang (2022) argued that those vaccines reduced the number of COVID-19 cases by 21%, the number of COVID-19 hospitalizations by 37%, and the number of COVID-19 deaths by 63%, or 34,900 (from January 2021 to May 2022).

In addition to analyzing the relationship between pharmaceutical innovation and mortality using national data, this study analyzed the relationship between access to drugs covered in public drug program formularies and mortality using data by province, disease, and year. The age-adjusted mortality rate from a given disease in a given province in a given year is significantly inversely related to the number of drugs that are used to treat that disease and that were

[11] As shown in Panel C of Table 4 and Figure 6, when $Y_{dt} = DAYS_{dt}$, the value of k for which β_k is most significant is k = 30: β_{30} = -0.511 (Z = 4.33).

covered in public drug program formularies in that province 4-12 years earlier, controlling for the average (across years) level of mortality and drug access of each disease in each province, the average (across provinces) level of mortality and drug access of each disease in each year, and the average (across diseases) level of mortality and drug access of each province in each year.

REFERENCES

Barter PJ, Waters DD (2018). Variations in time to benefit among clinical trials of cholesterol-lowering drugs. *J Clin Lipidol*. 12(4):857-862.

Bils M (2004). Measuring the growth from better and better goods. NBER working paper no. 10606, July.

Bresnahan TF, Gordon RJ, eds. (1997). *The Economics of New Goods*, v. 58 Studies in income and wealth, Chicago: University of Chicago Press.

Canadian Institute for Health Information Formulary coverage.

Centre National Hospitalier d'Information sur le Médicament (2024). Theriaque.

Grossman GM, Helpman E (1991). *Innovation and growth in the global economy*. Cambridge, MA: MIT Press.

Health Canada (2024). Drug Products Database.

Jovanovic *B,* Yatsenko *Y (*2012*).* Investment in vintage capital. *Journal of Economic Theory 147(2): 551-569.*

Kolata G (2024). An Obesity Drug Prevents Covid Deaths, Study Suggests. New York Times, August 30.

Lichtenberg F (2019). The impact of pharmaceutical innovation on the burden of disease in Canada, 2000-2016. *SSM - Population Health 8* (August).

NIH National Institute on Aging (2024). What Is Mild Cognitive Impairment?

OECD (2024a). OECD Data Explorer.

OECD (2024b). International shortlist for hospital morbidity tabulation.

Prince M, Patel V, Saxena S, et al (2007). No health without mental health. *Lancet* 370(9590): 859–77.

Statistics Canada (2024). Table 13-10-0801-01 Leading causes of death, total population (age standardization using 2011 population).

U.S. Centers for Disease Control and Prevention (2024). 113 ICD-10 Cause of Death Recode.

van de Glind EM, Willems HC, Eslami S, Abu-Hanna A, Lems WF, Hooft L, de Rooij SE, Black DM, van Munster BC (2016). Estimating the Time to Benefit for Preventive Drugs with the Statistical Process Control Method: An Example with Alendronate. *Drugs Aging* 33(5):347-53.

World Health Organization (2024). WHO Mortality Database.

WHO Collaborating Centre for Drug Statistics Methodology (2024). ATC structure and principles.

Wyonch R, Zhang T (2022). Damage Averted: Estimating the Effects of COVID-19 Vaccines on Hospitalizations, Mortality and Costs in Canada. Commentary 634. Toronto: C.D. Howe Institute.

TABLES AND CHARTS

Table 1

Estimates of β_k from eq. (1): $\ln(Y_{dt}) = \beta_k \ln(CUM\_DRUG_{d,t-k}) + \alpha_d + \delta_t + \varepsilon_{dt}$

lag	Est.	Std. Err.	Z	Pr > |Z|	trend	effect		Est.	Std. Err.	Z	Pr > |Z|	trend	effect
	A. $Y_{dt} = N\_DEATHS_{dt}$							B. $Y_{dt} = YLL85_{dt}$					
0	0.018	0.245	0.07	0.942	0.385	0.007		-0.302	0.271	-1.11	0.265	0.412	-0.124
2	-0.025	0.233	-0.11	0.914	0.435	-0.011		-0.307	0.273	-1.13	0.260	0.451	-0.138
4	-0.211	0.206	-1.03	0.305	0.542	-0.114		-0.386	0.261	-1.48	0.138	0.539	-0.208
6	-0.367	0.192	-1.91	0.056	0.565	-0.207		-0.431	0.232	-1.86	0.063	0.560	-0.241
8	**-0.411**	**0.204**	**-2.01**	**0.044**	**0.607**	**-0.250**		**-0.450**	**0.212**	**-2.13**	**0.034**	**0.577**	**-0.260**
10	-0.390	0.202	-1.93	0.053	0.645	-0.251		**-0.449**	**0.198**	**-2.27**	**0.023**	**0.616**	**-0.276**
12	**-0.363**	**0.183**	**-1.98**	**0.048**	**0.727**	**-0.264**		**-0.404**	**0.168**	**-2.41**	**0.016**	**0.701**	**-0.283**
14	**-0.430**	**0.197**	**-2.18**	**0.029**	**0.790**	**-0.340**		**-0.428**	**0.162**	**-2.65**	**0.008**	**0.750**	**-0.321**
16	**-0.499**	**0.212**	**-2.36**	**0.018**	**0.835**	**-0.417**		**-0.448**	**0.171**	**-2.61**	**0.009**	**0.810**	**-0.362**
18	**-0.547**	**0.210**	**-2.61**	**0.009**	**0.881**	**-0.482**		**-0.468**	**0.173**	**-2.70**	**0.007**	**0.850**	**-0.397**
20	**-0.606**	**0.208**	**-2.92**	**0.004**	**0.962**	**-0.583**		**-0.492**	**0.166**	**-2.96**	**0.003**	**0.928**	**-0.457**
22	**-0.581**	**0.189**	**-3.07**	**0.002**	**1.096**	**-0.636**		**-0.437**	**0.146**	**-2.99**	**0.003**	**1.072**	**-0.468**
24	**-0.533**	**0.162**	**-3.30**	**0.001**	**1.166**	**-0.621**		**-0.389**	**0.118**	**-3.29**	**0.001**	**1.144**	**-0.445**
26	**-0.493**	**0.149**	**-3.30**	**0.001**	**1.141**	**-0.562**		**-0.359**	**0.098**	**-3.65**	**0.000**	**1.150**	**-0.413**
28	**-0.414**	**0.124**	**-3.33**	**0.001**	**1.232**	**-0.510**		**-0.310**	**0.089**	**-3.50**	**0.001**	**1.226**	**-0.380**
30	**-0.361**	**0.116**	**-3.10**	**0.002**	**1.191**	**-0.430**		**-0.290**	**0.096**	**-3.03**	**0.002**	**1.210**	**-0.351**
	C. $Y_{dt} = YLL75_{dt}$							D. $Y_{dt} = YLL65_{dt}$					
0	-0.504	0.331	-1.52	0.128	0.401	-0.202		-0.777	0.434	-1.79	0.074	0.365	-0.284
2	-0.475	0.338	-1.40	0.160	0.439	-0.208		-0.718	0.436	-1.65	0.100	0.402	-0.289
4	-0.485	0.331	-1.46	0.143	0.518	-0.251		-0.679	0.420	-1.62	0.106	0.471	-0.320
6	-0.466	0.294	-1.58	0.113	0.539	-0.251		-0.608	0.357	-1.70	0.088	0.490	-0.298
8	-0.454	0.268	-1.69	0.091	0.553	-0.251		-0.565	0.313	-1.80	0.071	0.505	-0.285
10	-0.453	0.251	-1.80	0.071	0.592	-0.268		**-0.558**	**0.284**	**-1.97**	**0.049**	**0.544**	**-0.303**
12	**-0.417**	**0.204**	**-2.05**	**0.041**	**0.674**	**-0.281**		**-0.510**	**0.217**	**-2.35**	**0.019**	**0.620**	**-0.316**
14	**-0.425**	**0.192**	**-2.21**	**0.027**	**0.724**	**-0.308**		**-0.502**	**0.202**	**-2.49**	**0.013**	**0.678**	**-0.341**
16	**-0.438**	**0.202**	**-2.17**	**0.030**	**0.784**	**-0.343**		**-0.520**	**0.215**	**-2.42**	**0.016**	**0.733**	**-0.381**
18	**-0.464**	**0.203**	**-2.28**	**0.022**	**0.826**	**-0.383**		**-0.550**	**0.220**	**-2.50**	**0.012**	**0.786**	**-0.432**
20	**-0.486**	**0.192**	**-2.54**	**0.011**	**0.903**	**-0.439**		**-0.565**	**0.213**	**-2.65**	**0.008**	**0.859**	**-0.485**
22	**-0.430**	**0.169**	**-2.54**	**0.011**	**1.040**	**-0.448**		**-0.507**	**0.196**	**-2.58**	**0.010**	**0.978**	**-0.496**
24	**-0.377**	**0.144**	**-2.63**	**0.009**	**1.119**	**-0.422**		**-0.444**	**0.180**	**-2.46**	**0.014**	**1.071**	**-0.475**
26	**-0.355**	**0.127**	**-2.79**	**0.005**	**1.129**	**-0.401**		**-0.430**	**0.176**	**-2.44**	**0.015**	**1.082**	**-0.466**
28	**-0.305**	**0.120**	**-2.55**	**0.011**	**1.211**	**-0.370**		**-0.370**	**0.169**	**-2.19**	**0.028**	**1.182**	**-0.438**
30	**-0.289**	**0.131**	**-2.21**	**0.027**	**1.207**	**-0.349**		-0.345	0.183	-1.88	0.060	1.198	-0.413

Each estimate is from a separate regression. Estimates in bold are statistically significant (p-value < .05).

trend = weighted_mean[$\ln(CUM\_DRUG_{d,2022-k}/ CUM\_DRUG_{d,2000-k})$]. effect = β_k * trend.

Table 2

Estimates of π_k from eq. (2): $\ln(Y_{dt}) = \pi_k \ln(CUM\_CLASS_{d,t-k}) + \alpha_d + \delta_t + \varepsilon_{dt}$

lag	Est.	Std. Err.	Z	Pr > |Z|	trend	effect		Est.	Std. Err.	Z	Pr > |Z|	trend	effect
	A. $Y_{dt} = N\_DEATHS_{dt}$							B. $Y_{dt} = YLL85_{dt}$					
0	-0.427	0.403	-1.06	0.289	0.226	-0.097		-0.519	0.272	-1.91	0.057	0.236	-0.123
2	-0.616	0.400	-1.54	0.123	0.259	-0.159		**-0.645**	**0.283**	**-2.28**	**0.023**	**0.264**	**-0.170**
4	-0.725	0.379	-1.92	0.055	0.297	-0.215		**-0.749**	**0.291**	**-2.57**	**0.010**	**0.294**	**-0.220**
6	**-0.772**	**0.358**	**-2.16**	**0.031**	**0.326**	**-0.252**		**-0.804**	**0.295**	**-2.72**	**0.006**	**0.321**	**-0.258**
8	**-0.665**	**0.331**	**-2.01**	**0.045**	**0.343**	**-0.228**		**-0.792**	**0.292**	**-2.71**	**0.007**	**0.320**	**-0.253**
10	-0.497	0.287	-1.73	0.083	0.380	-0.189		**-0.691**	**0.283**	**-2.44**	**0.015**	**0.363**	**-0.251**
12	-0.294	0.197	-1.49	0.136	0.443	-0.130		-0.396	0.218	-1.82	0.070	0.448	-0.177
14	-0.194	0.168	-1.16	0.246	0.460	-0.089		-0.217	0.196	-1.11	0.269	0.457	-0.099
16	-0.083	0.160	-0.52	0.604	0.467	-0.039		-0.007	0.160	-0.04	0.966	0.491	-0.003
18	-0.013	0.172	-0.07	0.941	0.476	-0.006		0.077	0.144	0.54	0.592	0.500	0.039
20	-0.059	0.174	-0.34	0.735	0.614	-0.036		0.056	0.146	0.38	0.701	0.626	0.035
22	-0.120	0.165	-0.72	0.469	0.646	-0.077		0.007	0.142	0.05	0.962	0.669	0.005
24	-0.185	0.161	-1.15	0.252	0.678	-0.125		-0.055	0.144	-0.38	0.704	0.697	-0.038
26	-0.237	0.162	-1.47	0.142	0.720	-0.171		-0.100	0.146	-0.68	0.494	0.756	-0.075
28	-0.254	0.158	-1.61	0.108	0.882	-0.224		-0.125	0.132	-0.95	0.341	0.941	-0.118
30	-0.206	0.158	-1.30	0.192	0.920	-0.190		-0.121	0.118	-1.03	0.305	1.001	-0.121
	C. $Y_{dt} = YLL75_{dt}$							D. $Y_{dt} = YLL65_{dt}$					
0	**-0.694**	**0.320**	**-2.17**	**0.030**	**0.229**	**-0.159**		**-0.938**	**0.424**	**-2.21**	**0.027**	**0.208**	**-0.195**
2	**-0.769**	**0.350**	**-2.20**	**0.028**	**0.255**	**-0.196**		**-0.995**	**0.467**	**-2.13**	**0.033**	**0.232**	**-0.230**
4	**-0.838**	**0.372**	**-2.25**	**0.024**	**0.282**	**-0.236**		**-1.065**	**0.497**	**-2.14**	**0.032**	**0.254**	**-0.271**
6	**-0.873**	**0.381**	**-2.29**	**0.022**	**0.307**	**-0.268**		**-1.103**	**0.501**	**-2.20**	**0.028**	**0.277**	**-0.306**
8	**-0.863**	**0.386**	**-2.24**	**0.025**	**0.303**	**-0.262**		**-1.110**	**0.505**	**-2.20**	**0.028**	**0.277**	**-0.308**
10	**-0.789**	**0.390**	**-2.02**	**0.043**	**0.347**	**-0.274**		**-1.066**	**0.514**	**-2.07**	**0.038**	**0.316**	**-0.337**
12	-0.516	0.303	-1.70	0.089	0.433	-0.224		**-0.815**	**0.406**	**-2.01**	**0.045**	**0.398**	**-0.324**
14	-0.320	0.267	-1.20	0.230	0.440	-0.141		-0.579	0.363	-1.60	0.110	0.402	-0.233
16	-0.059	0.193	-0.31	0.760	0.488	-0.029		-0.195	0.273	-0.72	0.474	0.469	-0.091
18	0.032	0.162	0.20	0.842	0.506	0.016		-0.056	0.223	-0.25	0.804	0.507	-0.028
20	0.026	0.166	0.16	0.877	0.626	0.016		-0.041	0.226	-0.18	0.857	0.617	-0.025
22	-0.011	0.163	-0.07	0.944	0.669	-0.008		-0.063	0.220	-0.28	0.777	0.654	-0.041
24	-0.064	0.168	-0.38	0.704	0.697	-0.045		-0.108	0.228	-0.47	0.637	0.685	-0.074
26	-0.104	0.174	-0.60	0.549	0.754	-0.079		-0.152	0.239	-0.63	0.526	0.734	-0.111
28	-0.138	0.159	-0.87	0.385	0.933	-0.129		-0.200	0.222	-0.90	0.368	0.891	-0.178
30	-0.153	0.143	-1.07	0.283	0.992	-0.152		-0.238	0.202	-1.18	0.239	0.938	-0.224

Each estimate is from a separate regression. Estimates in bold are statistically significant (p-value < .05).

trend = weighted_mean[$\ln(CUM\_DRUG_{d,2022-k} / CUM\_DRUG_{d,2000-k})$]. effect = π_k * trend.

Table 3

Estimates of ρ_k from eq. (3):

$$\ln(AA\_MORT_{dpt}) = \rho_k \ln(N\_DRUG_{dp,t-k}) + \alpha_{dp} + \delta_{dt} + \phi_{pt} + \varepsilon_{dpt}$$

Lag	Estimate	Std. Err.	Z	Pr > |Z|
A. Quebec included				
0	0.031	0.047	0.66	0.509
2	0.007	0.041	0.16	0.872
4	**-0.059**	**0.022**	**-2.69**	**0.007**
6	-0.047	0.028	-1.70	0.088
8	-0.041	0.035	-1.19	0.232
10	**-0.121**	**0.048**	**-2.50**	**0.012**
12	**-0.116**	**0.047**	**-2.46**	**0.014**
14	-0.034	0.043	-0.79	0.428
16	-0.012	0.032	-0.37	0.709
18	-0.014	0.031	-0.47	0.639
B. Quebec excluded				
0	0.112	0.076	1.47	0.141
2	0.018	0.067	0.26	0.792
4	**-0.085**	**0.033**	**-2.58**	**0.010**
6	**-0.108**	**0.047**	**-2.30**	**0.022**
8	**-0.120**	**0.047**	**-2.53**	**0.012**
10	**-0.124**	**0.049**	**-2.53**	**0.012**
12	**-0.116**	**0.047**	**-2.46**	**0.014**
14	-0.034	0.043	-0.79	0.428
16	-0.012	0.032	-0.37	0.709
18	-0.014	0.031	-0.47	0.639

Each estimate is from a separate regression. Estimates in bold are statistically significant (p-value < .05).

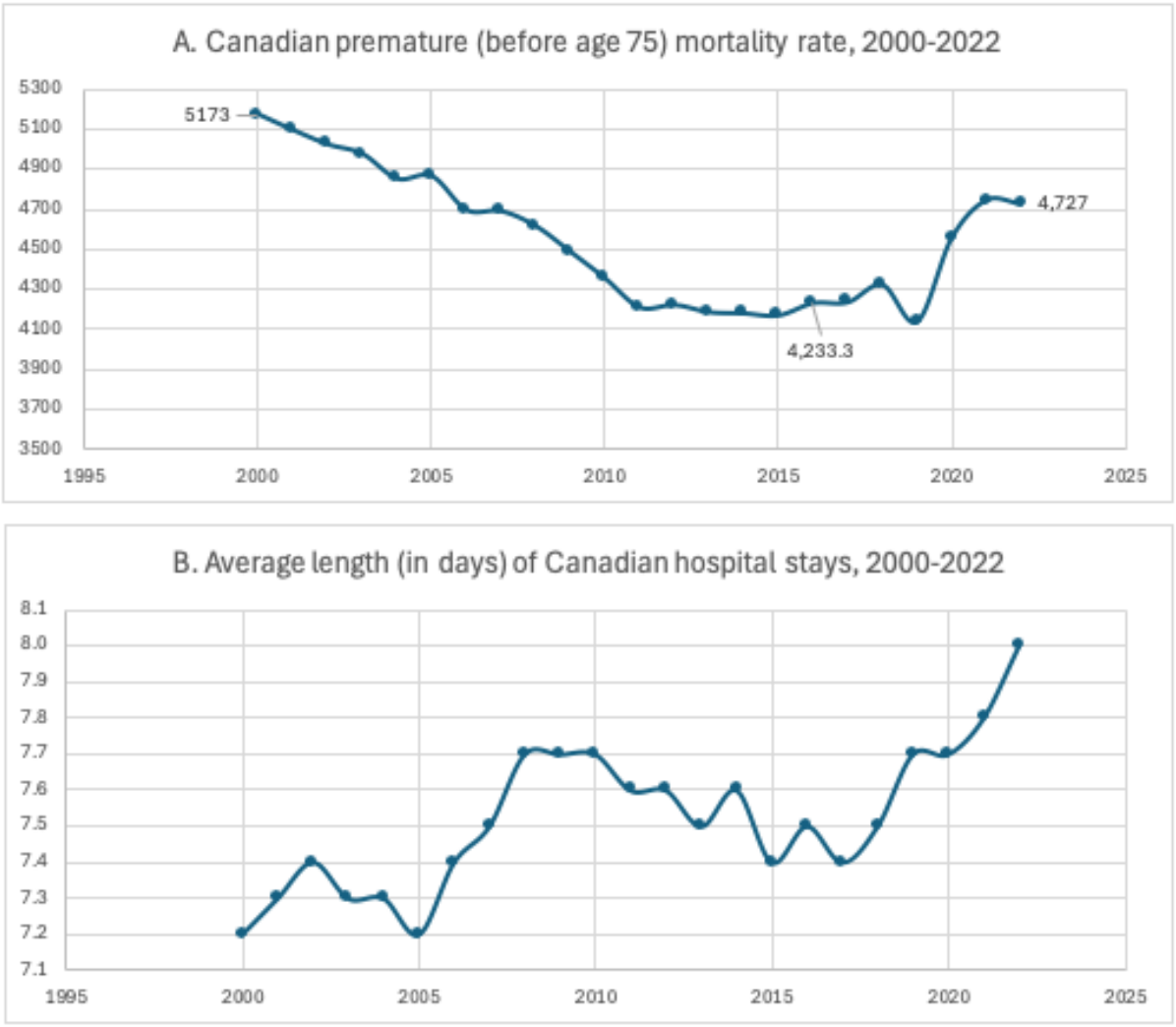
Table 4
Estimates of β_k from eq. (4): $\ln(Y_{dt}) = \beta_k \ln(CUM\_DRUG_{d,t-k}) + \alpha_d + \delta_t + \varepsilon_{dt}$

lag	Estimate	Std. Err.	Z	Pr > |Z|	trend	effect		Estimate	Std. Err.	Z	Pr > |Z|	trend	effect
	A. $Y_{dt} = DISCHARGES_{dt}$							B. $Y_{dt} = ALOS_{dt}$					
0	0.149	0.142	1.05	0.294	0.205	0.031		**-0.229**	**0.117**	**-1.95**	**0.051**	**0.207**	**-0.047**
2	0.088	0.119	0.74	0.462	0.262	0.023		-0.176	0.108	-1.62	0.105	0.260	-0.046
4	0.013	0.130	0.10	0.921	0.313	0.004		-0.171	0.108	-1.59	0.113	0.313	-0.053
6	-0.045	0.154	-0.29	0.769	0.346	-0.016		-0.156	0.110	-1.42	0.156	0.341	-0.053
8	-0.077	0.163	-0.47	0.635	0.390	-0.030		-0.139	0.112	-1.24	0.216	0.387	-0.054
10	-0.086	0.132	-0.65	0.515	0.442	-0.038		-0.111	0.105	-1.06	0.291	0.439	-0.049
12	-0.087	0.107	-0.81	0.418	0.493	-0.043		-0.093	0.089	-1.05	0.295	0.494	-0.046
14	-0.081	0.100	-0.81	0.418	0.535	-0.043		-0.101	0.075	-1.34	0.179	0.537	-0.054
16	-0.059	0.101	-0.59	0.558	0.567	-0.034		-0.103	0.067	-1.54	0.124	0.570	-0.059
18	0.024	0.096	0.25	0.801	0.651	0.016		**-0.121**	**0.056**	**-2.16**	**0.031**	**0.642**	**-0.077**
20	0.071	0.102	0.69	0.491	0.734	0.052		**-0.140**	**0.052**	**-2.71**	**0.007**	**0.723**	**-0.101**
22	0.065	0.106	0.61	0.540	0.834	0.054		**-0.163**	**0.050**	**-3.28**	**0.001**	**0.832**	**-0.135**
24	0.037	0.111	0.34	0.737	0.893	0.033		**-0.159**	**0.052**	**-3.09**	**0.002**	**0.886**	**-0.141**
26	-0.036	0.109	-0.33	0.744	0.847	-0.030		**-0.152**	**0.053**	**-2.86**	**0.004**	**0.862**	**-0.131**
28	-0.128	0.117	-1.09	0.274	0.898	-0.115		**-0.127**	**0.058**	**-2.18**	**0.029**	**0.917**	**-0.117**
30	-0.169	0.119	-1.42	0.155	0.907	-0.153		-0.104	0.059	-1.78	0.075	0.920	-0.096
	C. $Y_{dt} = DAYS_{dt}$												
0	**-0.526**	**0.197**	**-2.67**	**0.008**	**0.236**	**-0.124**							
2	**-0.371**	**0.170**	**-2.19**	**0.029**	**0.299**	**-0.111**							
4	**-0.359**	**0.166**	**-2.16**	**0.031**	**0.336**	**-0.121**							
6	-0.310	0.171	-1.81	0.070	0.384	-0.119							
8	-0.255	0.181	-1.41	0.158	0.435	-0.111							
10	-0.210	0.171	-1.23	0.220	0.490	-0.103							
12	-0.189	0.152	-1.25	0.213	0.542	-0.103							
14	-0.203	0.139	-1.46	0.146	0.578	-0.117							
16	-0.218	0.128	-1.70	0.089	0.602	-0.131							
18	**-0.234**	**0.118**	**-1.97**	**0.049**	**0.655**	**-0.153**							
20	**-0.290**	**0.131**	**-2.21**	**0.027**	**0.709**	**-0.205**							
22	**-0.359**	**0.144**	**-2.50**	**0.013**	**0.802**	**-0.288**							
24	**-0.434**	**0.155**	**-2.80**	**0.005**	**0.827**	**-0.358**							
26	**-0.499**	**0.152**	**-3.28**	**0.001**	**0.828**	**-0.413**							
28	**-0.527**	**0.131**	**-4.03**	**<.0001**	**0.861**	**-0.454**							
30	**-0.511**	**0.118**	**-4.33**	**<.0001**	**0.849**	**-0.434**							

Each estimate is from a separate regression. Estimates in bold are statistically significant (p-value < .05).
trend = weighted_mean[$\ln(CUM\_DRUG_{d,2022-k}/ CUM\_DRUG_{d,2000-k})$]. effect = π_k * trend.

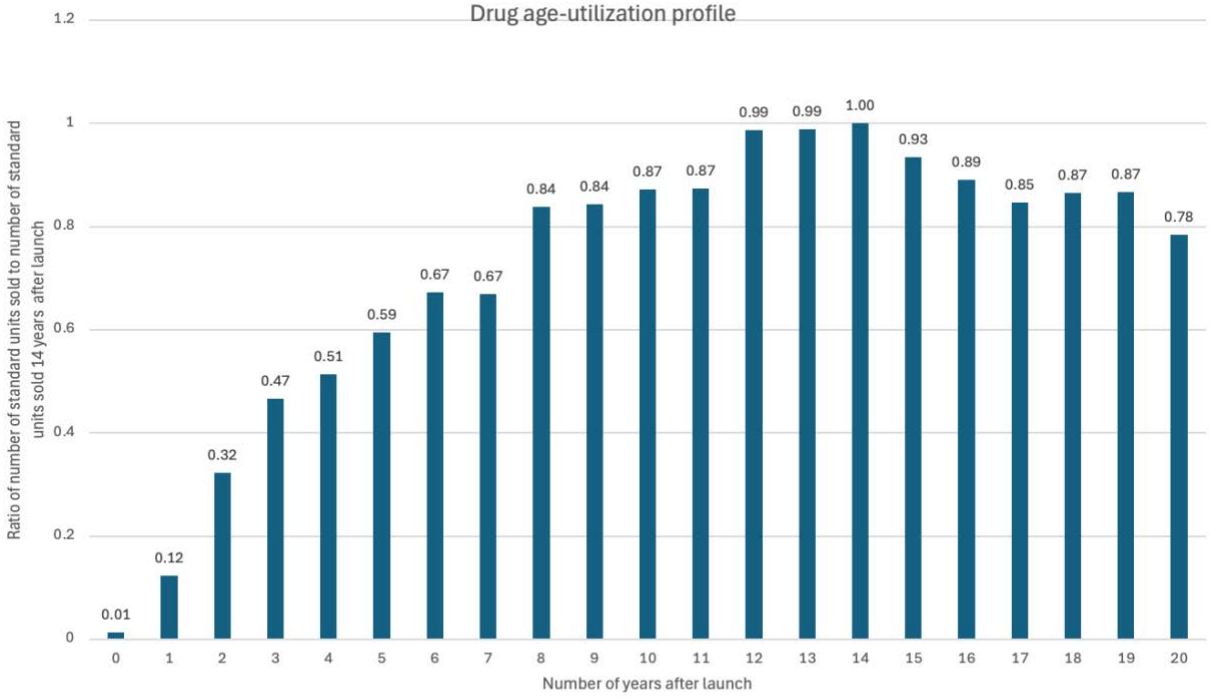
Figure 1

Premature mortality and average length of hospital stays in Canada, 2000-2022



Source: OECD Data Explorer, https://data-explorer.oecd.org/

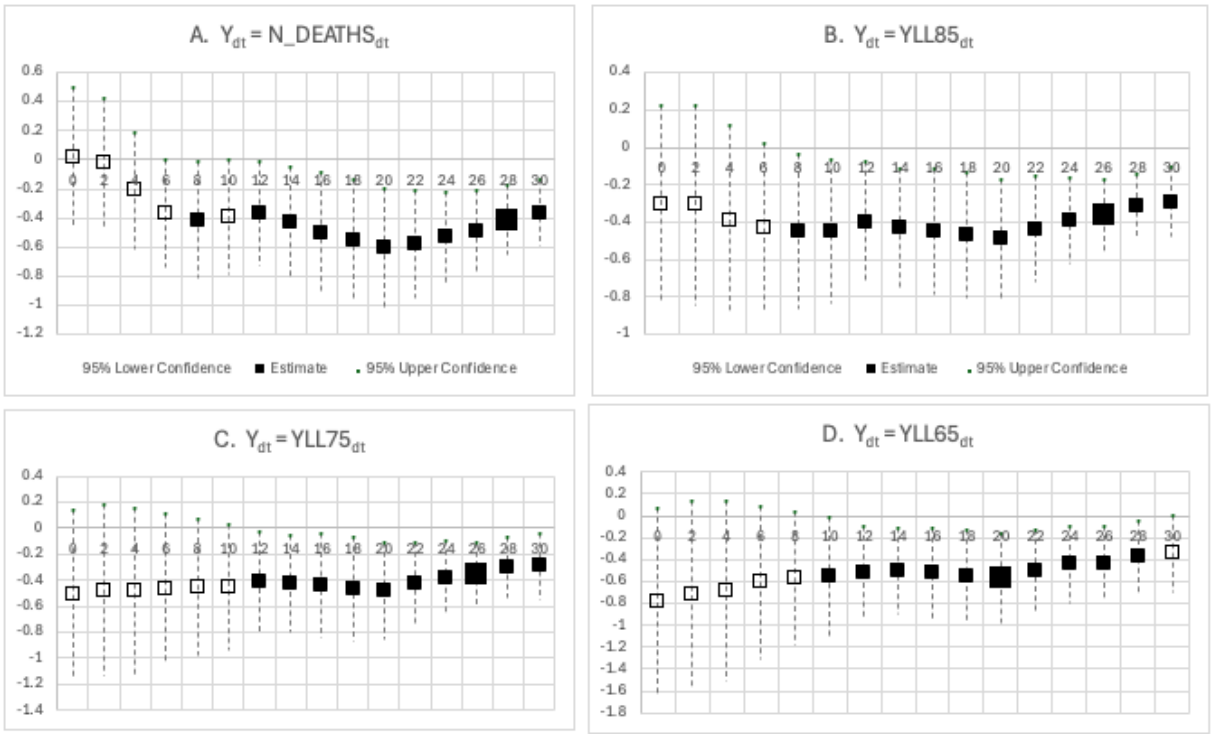
Figure 2
Drug age-utilization profile



Source: Lichtenberg (2019). Author's calculations based on data contained in Health Canada Drug Product Database and IQVIA MIDAS database.

Figure 3

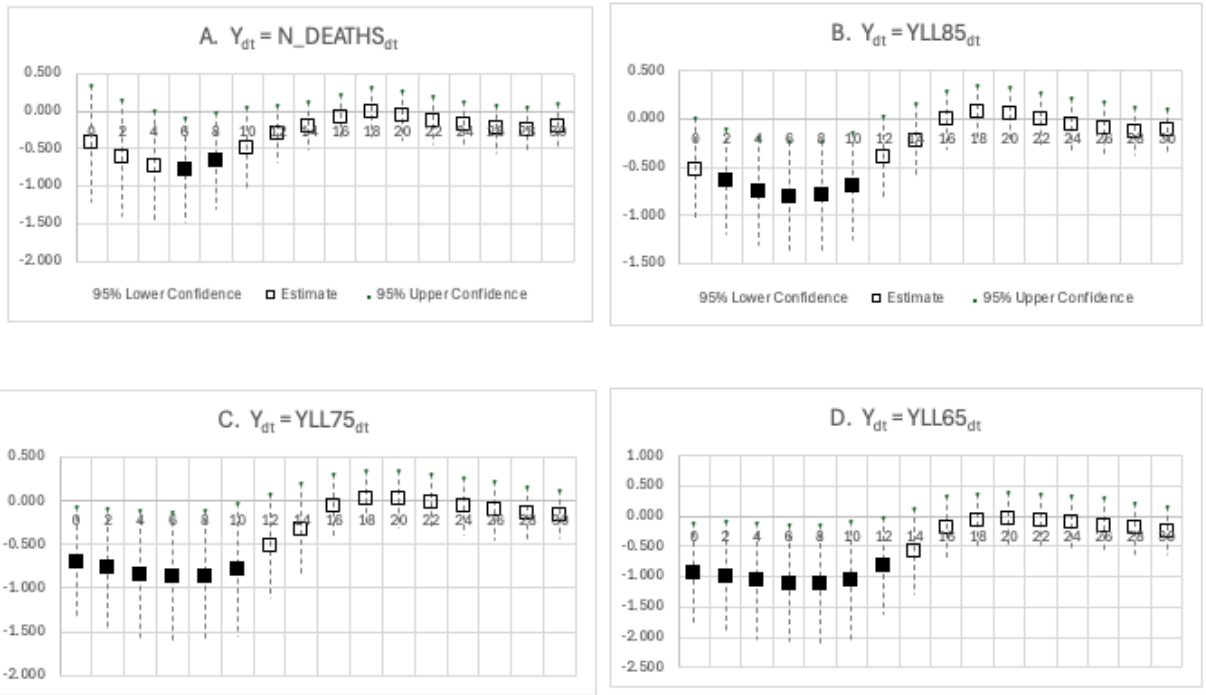
Estimates of β_k from eq. (1): $\ln(Y_{dt}) = \beta_k \ln(CUM\_DRUG_{d,t-k}) + \alpha_d + \delta_t + \varepsilon_{dt}$



Solid squares denote statistically significant estimates (p-value < .05). Hollow squares denote insignificant estimates.

Figure 4

Estimates of π_k from eq. (2): $\ln(Y_{dt}) = \pi_k \ln(CUM\_CLASS_{d,t-k}) + \alpha_d + \delta_t + \varepsilon_{dt}$

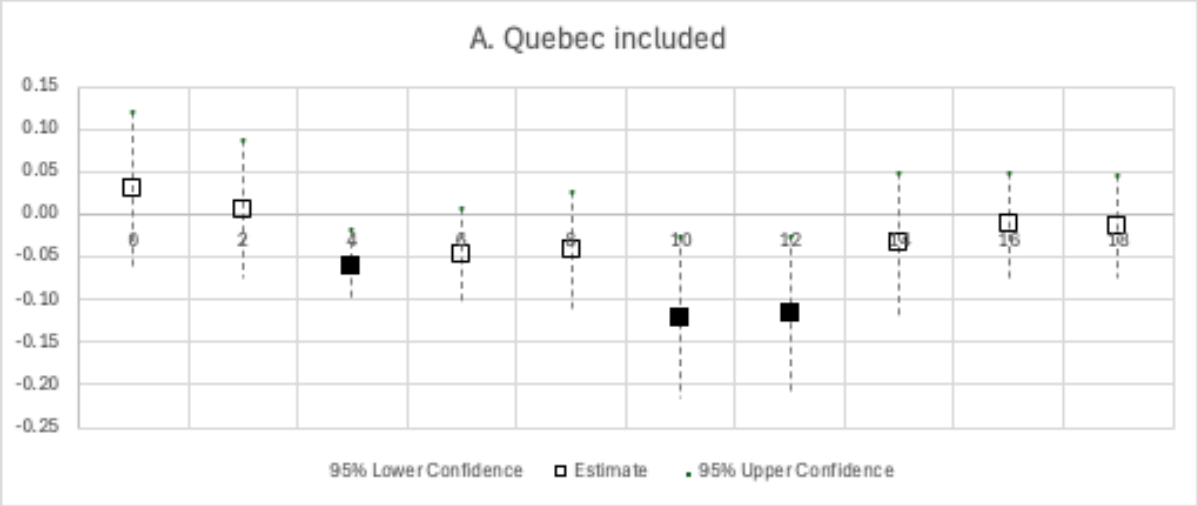


Solid squares denote statistically significant estimates (p-value < .05). Hollow squares denote insignificant estimates.

Figure 5

Estimates of ρ_k from eq. (3):

$$\ln(AA\_MORT_{dpt}) = \rho_k \ln(N\_DRUG_{dp,t-k}) + \alpha_{dp} + \delta_{dt} + \phi_{pt} + \varepsilon_{dpt}$$



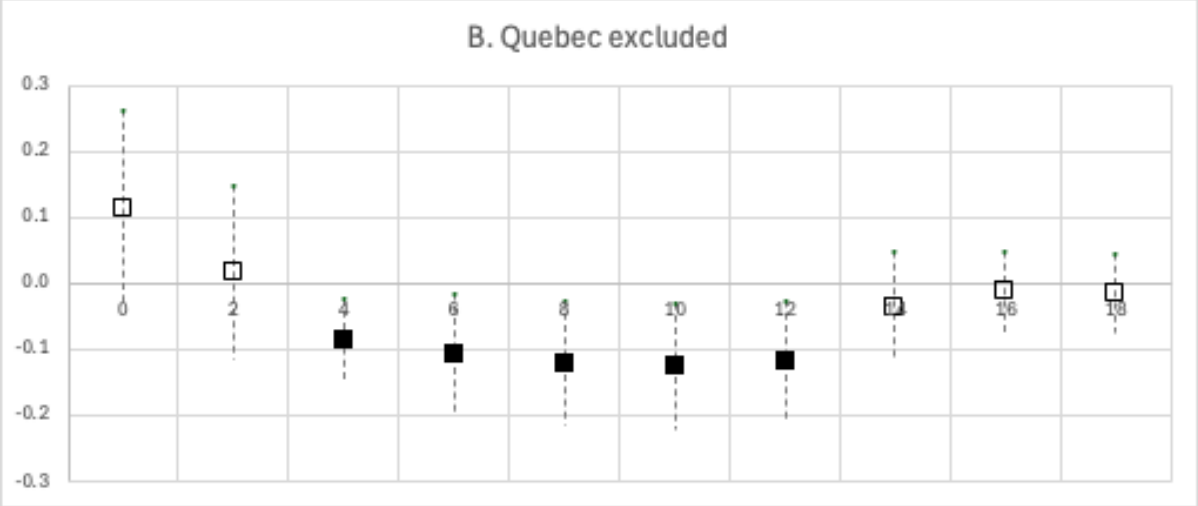


Figure 6

Estimates of β_k from eq. (4): $\ln(Y_{dt}) = \beta_k \ln(CUM\_DRUG_{d,t-k}) + \alpha_d + \delta_t + \varepsilon_{dt}$

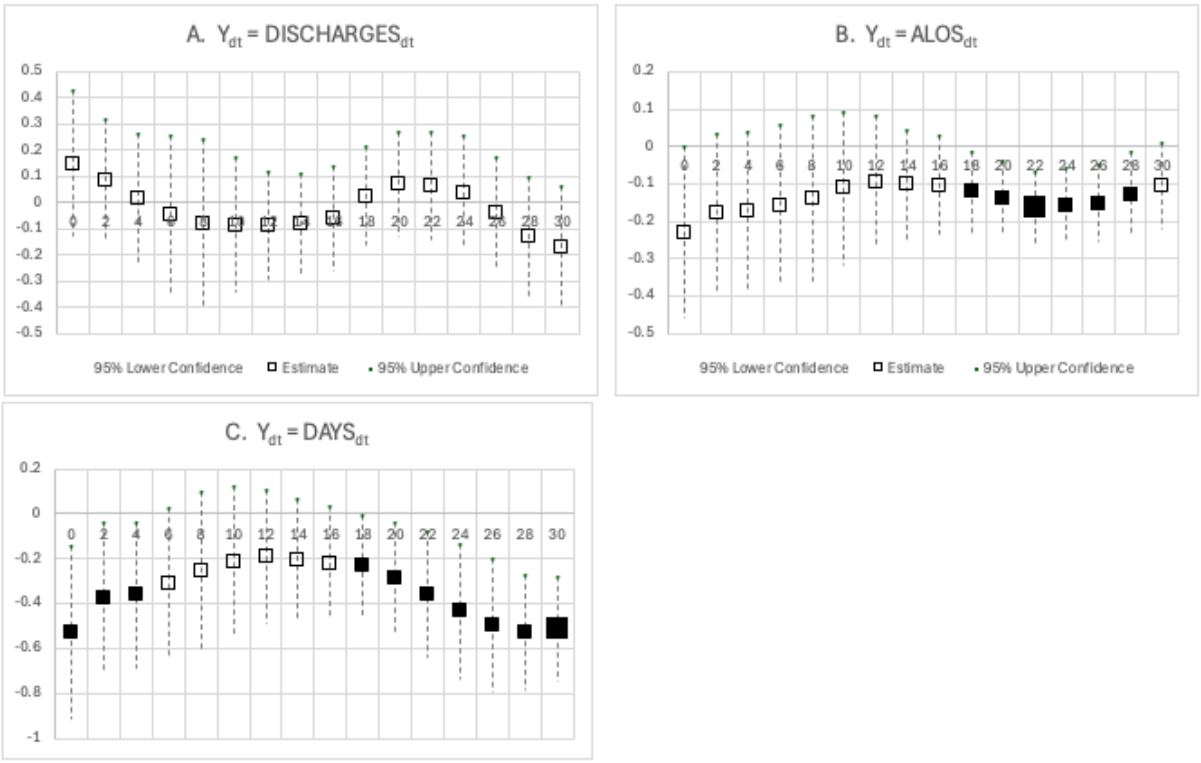
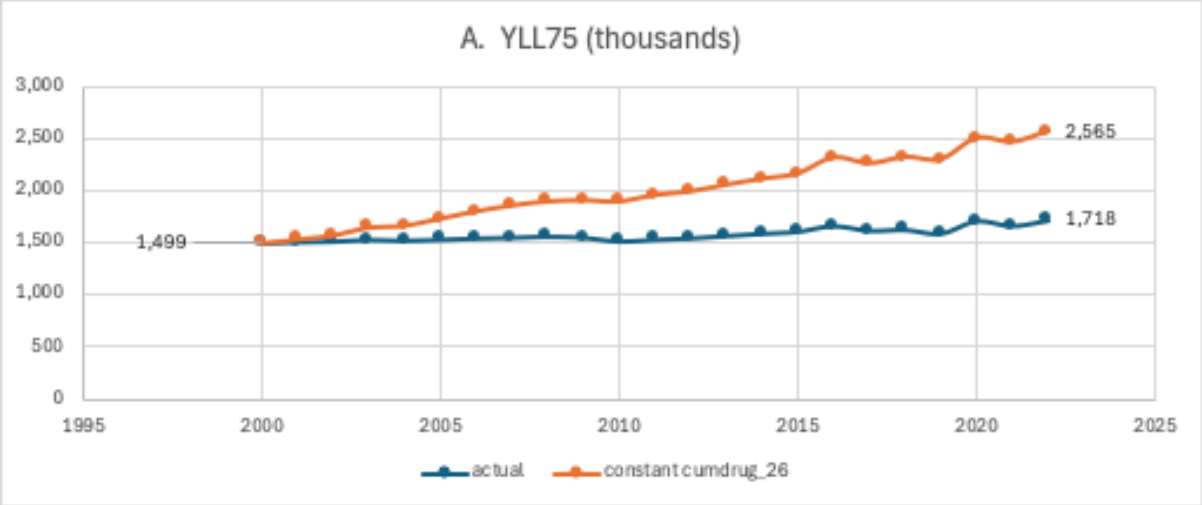
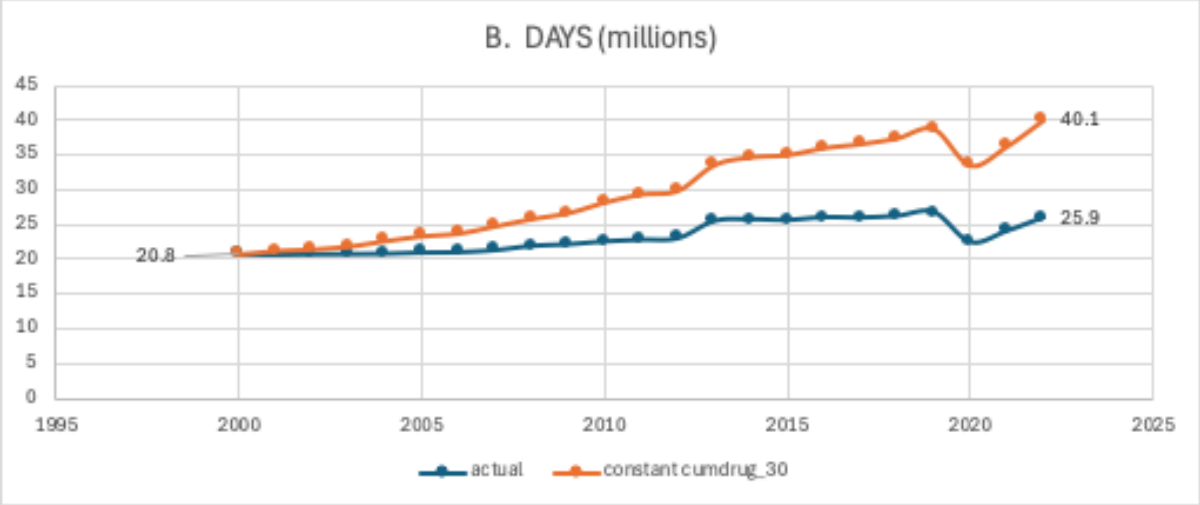


Figure 7

2000-2022 growth in YLL75 and DAYS in the presence and absence of previous drug approvals





Appendix Table 1

Disease classification used in Statistics Canada Table 13-10-0801-01 Leading causes of death, total population (age standardization using 2011 population)

ICD10	Leading_causes_of_death__ICD_10
A00-Y89	Total, all causes of death [A00-Y89]
A01-A02	Salmonella infections [A01-A02]
A03, A06	Shigellosis and amoebiasis [A03, A06]
A16-A19	Tuberculosis [A16-A19]
A37	Whooping cough [A37]
A38, A46	Scarlet fever and erysipelas [A38, A46]
A39	Meningococcal infection [A39]
A40-A41	Sepsis [A40-A41]
A50-A53	Syphilis [A50-A53]
A80	Acute poliomyelitis [A80]
A83-A84, A85.2	Arthropod-borne viral encephalitis [A83-A84, A85.2]
B05	Measles [B05]
B15-B19	Viral hepatitis [B15-B19]
B20-B24	Human immunodeficiency virus [HIV] disease [B20-B24]
B50-B54	Malaria [B50-B54]
C00-C97	Malignant neoplasms [C00-C97]
D00-D48	In situ neoplasms, benign neoplasms and neoplasms of uncertain or unknown behaviour [D00-D48]
D50-D64	Anaemias [D50-D64]
E10-E14	Diabetes mellitus [E10-E14]
E40-E64	Nutritional deficiencies [E40-E64]
G00, G03	Meningitis [G00, G03]
G20-G21	Parkinson's disease [G20-G21]
G30	Alzheimer's disease [G30]
I00-I09, I11, I13, I20-I51	Diseases of heart [I00-I09, I11, I13, I20-I51]
I10, I12, I15	Essential hypertension and hypertensive renal disease [I10, I12, I15]
I60-I69	Cerebrovascular diseases [I60-I69]
I70	Atherosclerosis [I70]
I71	Aortic aneurysm and dissection [I71]
J09-J18	Influenza and pneumonia [J09-J18]
J20-J21	Acute bronchitis and bronchiolitis [J20-J21]
J40-J47	Chronic lower respiratory diseases [J40-J47]
J60-J66, J68	Pneumoconioses and chemical effects [J60-J66, J68]
J69	Pneumonitis due to solids and liquids [J69]
K25-K28	Peptic ulcer [K25-K28]
K35-K38	Diseases of appendix [K35-K38]
K40-K46	Hernia [K40-K46]
K70, K73-K74	Chronic liver disease and cirrhosis [K70, K73-K74]
K80-K82	Cholelithiasis and other disorders of gallbladder [K80-K82]
N00-N07, N17-N19, N25-N27	Nephritis, nephrotic syndrome and nephrosis [N00-N07, N17-N19, N25-N27]
N10-N12, N13.6, N15.1	Infections of kidney [N10-N12, N13.6, N15.1]
N40	Hyperplasia of prostate [N40]
N70-N76	Inflammatory diseases of female pelvic organs [N70-N76]
O00-O99	Pregnancy, childbirth and the puerperium [O00-O99]
P00-P96	Certain conditions originating in the perinatal period [P00-P96]
Q00-Q99	Congenital malformations, deformations and chromosomal abnormalities [Q00-Q99]
U07.1, U07.2, U10.9	COVID-19 [U07.1, U07.2, U10.9]
V01-X59, Y85-Y86	Accidents (unintentional injuries) [V01-X59, Y85-Y86]
X60-X84, Y87.0	Intentional self-harm (suicide) [X60-X84, Y87.0]
X85-Y09, Y87.1	Assault (homicide) [X85-Y09, Y87.1]
Y35, Y89.0	Legal intervention [Y35, Y89.0]
Y36, Y89.1	Operations of war and their sequelae [Y36, Y89.1]
Y40-Y84, Y88	Complications of medical and surgical care [Y40-Y84, Y88]

Appendix Table 2

Number of (5th-level, WHO ATC) chemical substances covered by public drug formularies, by jurisdiction and year

year	Alberta	British Columbia	Manitoba	New Brunswick	Newfoundland and Labrador	Nova Scotia	Ontario	Prince Edward Island	Quebec	Saskatchewan	Yukon
1995	739	829	905	384							
1996	750	844	929	410							
1997	741	818	950	433							
1998	739	823	971	449							
1999	782	782	998	471							
2000	786	779	1014	483				452			
2001	785	822	1020	492				452		683	
2002	775	802	1022	499				452		705	
2003	756	826	1037	570			647	500	2	712	
2004	740	905	1039	594	889	751	651	521	2	723	
2005	733	919	1041	631	941	750	645	549	2	733	
2006	706	927	1046	651	865	732	639	591	5	650	
2007	691	933	1044	672	875	744	621	639	7	659	
2008	650	941	1041	687	883	753	591	669	11	666	
2009	659	953	1041	710	901	766	602	676	13	689	
2010	653	961	953	725	908	769	603	670	56	693	
2011	659	973	938	730	914	776	593	670	87	705	
2012	665	986	940	741	933	838	603	692	143	719	
2013	672	985	939	757	943	852	609	636	295	731	
2014	672	995	984	785	969	870	620	665	318	742	766
2015	679	993	909	810	995	889	717	690	363	763	801
2016	683	987	932	834	1029	801	763	695	428	778	825
2017	689	1028	955	846	860	802	775	695	486	797	853
2018	699	1042	936	863	861	799	836	711	633	813	862
2019	708	1017	932	881	874	827	844	713	746	826	865
2020	704	965	924	898	863	845	852	691	844	837	918

Source: author's calculations based on data in Canadian Institute for Health Information. Formulary coverage. https://www.cihi.ca/sites/default/files/document/formulary-coverage-data-table-en.xlsx