Quantifying the Economic Impacts of COVID-19 Policy Responses on Canada's Provinces In (Almost) Real Time

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ABSTRACT. We develop a methodology to track and quantify the economic impacts of lock-down and re-opening policies by Canadian provinces in response to the COVID-19 pandemic, using data that is available with a relatively short time-lag. To do so, we adapt, calibrate and implement a dynamic, seasonally-adjusted, input-output model with supply constraints. Our framework allows us to quantify potential scenarios for the impacts of lock-down and reopening which allow for dynamic complementarities between industries, seasonal fluctuations, and changes in the composition of demand. Taking account of the observed variation in re-opening strategies across provinces, we estimate the costs of the policy response in term of lost hours of employment and production.

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COVID-19 is an unusual macroeconomic shock. It cannot easily be categorized as an aggregate supply or demand shock. Rather, it is a messy combination of disaggregated supply and demand shocks. These shocks propagate through supply chains to create different cyclical conditions in different parts of the economy. Some sectors are tight, constrained by supply constraints, and struggling to keep up with demand. Other sectors are slack and shedding workers to reduce excess capacity because of lack of demand.

- Baquee and Farhi (2020a)

1. INTRODUCTION

The World Health Organization named the COVID-19 outbreak a pandemic on March 11, 2020. Over the weeks that followed, federal and provincial governments across Canada took unprecedented steps to slow the rate at which the virus was spreading. Ontario, for example, announced the closure of schools on March 12, the closure of bars, restaurants, and recreational facilities on March 17, and the closure of all non-essential workplaces on March 23. By mid-April, it was clear that most locations in Canada had succeeded in "flattening the curve," spreading out the potential duration of the pandemic but ensuring that disease rates at any point in time did not overrun hospital capacity.

At that point, the policymakers started to consider whether and how to relax lockdown restrictions and reopen the economy. Such decisions should account for both the costs of relaxing lock-down restrictions, in terms of COVID-19 illnesses and deaths, as well as the benefits, in term of effects on employment and GDP and long-run well-being measures. However, the costs and benefits of alternative strategies were not equally salient. While there is real-time data on COVID-19 cases and deaths, data on economic outcomes, such as employment income and GDP by industry and province, and other measures such as test scores assessing student learning, are relatively delayed. For example, national estimates of GDP by industry become available from Statistics Canada after a two month lag and provincial estimates after an even longer period.¹

Furthermore, while well-established epidemiological models were designed to forecast the spread of the disease and mortality during pandemics, most economic models were not designed for pandemics. As such, policymakers faced clear estimates of the direct benefits of continuing strict lock-down policies, but less precise claims about the

¹The lag reflects the gathering of data from the Monthly Survey of Manufacturing and the Survey of Employment, Payrolls and Hours (SEPH).

economic costs of doing so.² These factors likely contributed to continuation of strict lock-down policies for another month or more following the flattening of the curve, even in communities that reported no new cases during this period. British Columbia did not begin to reopen its economy until May 6, and Ontario did not begin to do so until May 19, starting a months-long process of relaxing lock-down restrictions. Other provinces faced similar delays in reopening.

This experience with COVID-19 has highlighted the need for economic models that can rapidly help guide regional policy during times of pandemics or other crises. In this paper, we propose one such model that builds on recent research modeling the economic impact of natural disasters. Our model tracks how the pandemic and corresponding lock-down policies have affected regional economic outcomes, such as jobs, hours worked and GDP to date, and provides forecasts projecting these outcomes into the months ahead as the economy recovers from the initial shocks. The model is easily adaptable to account for the specific characteristics of alternative crises and various scenarios that may play out during a downturn and economic recovery process. Finally, the model relies on public data that is collected and released with a relatively short time-lag, allowing for frequent updates to provide policymakers with most-recent information.

Specifically, we adapt, calibrate and implement a dynamic, seasonally-adjusted, inputoutput model with supply constraints, which allows us to quantify the impact of economywide shocks stemming from severe hits to production in a subset of industries, while accounting for dynamic complementarities between industries, seasonal fluctuations, and changes in the composition of demand. Taking account of the observed variation in reopening strategies across provinces we estimate the costs of the policy response in terms of lost hours of employment, jobs and income from production.

Our model builds on recent developments involving dynamic Input-Output models, developed to assess the economic impacts of natural disasters (e.g., Akhtar and Santos, 2013; Hallegate, 2014; Okuyama and Santos, 2014; Avelino and Hewings, 2019). Specifically, it builds on the Generalized Dynamic Input-Output (GDIO) model due to Avelino and Hewings (2019). We adapt this framework to consider month-to-month dynamics in a setting where temporary economic shutdown measures, such as those associated with COVID-19 lock-down policies, may initially constrain production. We refer to this adaptation as the Short-Term Under-capacity Dynamic Input-Output (STUDIO) model.

²For example, on April 3, the government of Ontario projected that the province could see between 3,000 to 15,000 deaths related to COVID-19 given its lock-down restrictions, while the death toll may have been as high as 100,000 without the government restrictions. https://www.cbc.ca/news/canada/toronto/ontario-COVID-projections-1.5519575

The STUDIO model captures the interconnection between geographies and industries, which we calibrate using Input-Output (IO) Summary Tables, inter-provincial and international trade flow data and labour market data from Statistics Canada. We then use the framework to estimate the economic impact of COVID-19 over a 12-month period under alternative forward-looking scenarios about the speed of recovery, government policy, and medium-to-long term changes in consumer preferences.

Labour market restrictions during the lock-down are calibrated to replicate observed changes in hours worked and employment for each of the industries using data from the monthly Labour Force Survey (LFS). We use these to compute the immediate impacts on production outcomes. Output of and employment by a given producer depends on both the demand for its goods and services from downstream producers and the supply of inputs available from upstream ones. Consequently, the speed of recovery for any one industry depends on its input-output interactions with others that may continue to be constrained, even if that industry is not. Our model captures these interactions to allow a full assessment of the impacts of each scenario.

Under our "optimistic scenario," which assumes that demand will return to its pre-COVID level by the end of 2020, we estimate that across all provinces, Canada will experience a GDP loss exceeding 170 billion CAD between March 2020 and February 2021 as a result of COVID-19. This represents an approximate 8.3% shortfall in Canadian GDP relative to what was otherwise predicted for this period. These estimates are aggregated from monthly provincial industry level estimates, which themselves vary considerably.³

In addition to our optimistic scenario, we consider several other possibilities, including recovery scenarios in which consumers behavior in the post-COVID economy does not converge during recovery to the pre-COVID levels but instead sees continued declines in consumer confidence, recreational activities, or tourism. We also develop a second wave scenario that reflects the concerns of epidemiologists and policymakers that new lock-downs may be required in the fall. We use the model to translate these alternative scenarios into economic cost estimates that can potentially be used to inform decision-making. For example, the cost of measures taken today to mitigate the transmission of the virus may be compared with the losses incurred during future lock-downs that result from not taking them.

There is already a burgeoning literature that studies, both empirically and theoretically, various aspects of the economic implications of the COVID-19 pandemic, especially in the US. Many of these merge epidemiological and economic modeling to undertake

³Our analysis only focuses on Canadian provinces and does not include territories. Note that despite their physical size, the economies of the three territories combined (Northwest Territories, Yukon and Nunavut) contribute approximately 0.5% of Canadian GDP.

policy analysis for the pandemic.⁴ While recognizing that different sectors of the economy are impacted more than others, most papers do not study the resulting dynamic input-output interactions that arise as constraints on different sectors of the economy are tightened and relaxed.

Several papers study these potential interactions in theory. In particular, Guerrieri et al. (2020) show how negative supply shocks can have negative demand spillovers, under the condition that the inter-sectoral elasticity of substitution is less than the inter-temporal one. Baqaee and Farhi (2020b) show that complementarities in the production network can also amplify negative supply shocks, even if the inter-sectoral and inter-temporal elasticities of substitution in consumption are the same.⁵ In their analysis of the nonlinear mapping, implied by a generalized I-O framework, from changes in hours and household preferences to real GDP, Baqaee and Farhi (2020a) find that the negative supply and demand shocks associated with COVID-19 are large enough that accounting for non-linearity is quantitatively important.

Here we focus explicitly on the quantitative *dynamic* input-output interactions between industrial sectors resulting from the lock-down and recovery policies followed by federal and provincial governments in Canada. The intent has been to rapidly provide a usable framework for policy-planning and scenario development. In doing so we have simplified by abstracting from optimal savings behaviour of households, the direct interactions with epidemiological models and possibilities of input substitution and technological adaptions. In future work, we plan to develop extensions that incorporate these features.

The remainder of this articles proceeds as follows. In Section 2, we describe informally the key features of our adaptation of the GDIO model, leaving most of the formal details to the Appendix. We also detail our parameterization of the model and various scenarios that we consider. In Section 3, we provide the main results in each scenario, including the estimated overall losses by province in terms of hours of work and GDP. Section 4 concludes and discusses further work.

⁴Acemoglu et al. (2020), Alvarez, Argente, and Lippi (2020), Atkeson (2020a, b), Aum, Lee, and Shin (2020), Azzimonti et al. (2020), Baqaee and Farhi (2020a, b), Baqaee, Farhi, Mina and Stock (2020), Berger, Herkenhoff, and Mongey (2020), Bodenstein, Crosetti, and Guerrieri (2020), Budish (2020), Eichenbaum, Rebelo, and Trabant (2020a,b), Farboodi, Jarosch, and Shimer (2020), Favero, Ichino, and Rustichini (2020), Glover et al. (2020), Guerrieri et al. (2020), Jones, Philippon, and Venkateswaran (2020), Krueger, Uhlig, and Xie (2020), Lin and Meissner (2020), Ludvigson, Ma, and Ng (2020), Morris et. al. (2020), Moser and Yared (2020), Mulligan (2020), Rampini (2020), Rio-Chanona et al. (2020), and Stock (2020).

⁵They also show that while complementarities amplify negative supply shocks, they also mitigate negative demand shocks.

2. The Model

2.1. The Basic Framework. Our core model builds on the GDIO model developed by Avelino and Hewings (2019). Input-Output (IO) models use regional Input-Output tables, commonly provided by statistical agencies, to represent the production structure of the economy. Consequently, they emphasize the cross-industry interactions that result from each industry's use of intermediate inputs produced by other industries. The GDIO model is one of a class of dynamic IO models that have been developed to study various kinds of major external shocks such as natural disasters (e.g. hurricanes and earthquakes). The core dynamics of the GDIO model arise from the asynchronicity between the production of intermediate inputs in some sectors and their subsequent use in other sectors, and the resulting evolution of inventories of finished goods. This differs from standard "static" IO models, which are typically conceptualized as representing an entire year so that there is no "delay" between input production and use, and inventories are entirely exogenous. An important feature of the GDIO model and other related frameworks is that they allow for the impacts of both supply-side constraints and demand fluctuations and the dynamic interactions between them.

We lay out the formal details of the model in the Appendix. The mechanics of the model are essentially driven by managers with limited information trying to match their production with expected demand in a context where prices are not adjusting to clear the market. Managers first determine the feasibility of their production schedules for the period, given the current availability of industrial inputs and labor hours. If the total schedule is not feasible, producers must ration supply to users in excess of any inventories from the previous period. As a result, depending on labor market conditions, household income and unemployment, final demand might be under- or over-supplied. Managers react to this supply-demand imbalance by adjusting their expectations for the next production cycle, and by attempting to purchase the necessary level of inputs. Because this inter-industrial demand may also be under- or oversupplied, after markets clear, managers in each sector determine a feasible production schedule for the upcoming period (Avelino and Hewings, 2019).

We refer to our version of the GDIO model as the Short-Term Under-capacity Dynamic Input-Output (STUDIO) model. This reflects our focus on month-to-month dynamics in a situation where lock-down policies may initially constrain production below that which could be produced given the available capital stock. Specifically, we model lockdowns by explicitly imposing labour constraints in the production function. In addition, we allow for endogenous demand-side effects coming from increased unemployment via a simple household expenditure model. Specifically, we assume that total final consumption demand is given by a time-varying fraction, $\Phi(t)$, of total current income:

$$C(t) = \Phi(t) \left(\sum_{j} w_j(t) H_j(t) + \left(\bar{L}(t) - \sum_{j} L_j(t) \right) b(t) + \Omega^o(t) \right), \tag{1}$$

where $w_j(t)$ denotes the wage per hour in industry *j*, $H_j(t)$ represents total hours worked, $\bar{L}(t)$ denotes total available labour supply, $L_j(t)$ denotes total labour used by industry *j*, b(t) denotes transfers received while unemployed and $\Omega^o(t)$ represent other, non-labour income. While we do not model optimal dynamic consumption behaviour, this flexible specification is intended to allow for variation in the propensity to consume out of current income resulting from expected wealth effects.

The STUDIO model is therefore intended for developing scenarios involving shortterm dynamics, especially those associated with labour market restrictions like those imposed by the lock-down.⁶ It is not well-suited for studying longer-term dynamics, over several years, because the model does not account for price and wage changes, nor the future impact of capital accumulation or technological change that results from current activities. As argued by Oosterhaven and Bouwmeester (2016), the assessment of longer term regional impacts should be based on a computable general equilibrium (CGE) framework. IO models have the advantages of rapid implementation, tractability and integration flexibility with external models that may be essential in the context of pandemics. The trade-off is the imposition of more rigid assumptions on substitutability between goods and factors, price changes and functional forms, which make IO more appropriate for short/medium term analysis.⁷ In the case of the COVID-19 scenarios considered here, the model economy recovers within several months following the relaxation of lock-down policies and, therefore, we believe a medium-term horizon allows for a reasonable estimation of the main impacts of the pandemic on the economy.

2.2. International and inter-provincial trade flows. We treat each province as a small open economy that engages in trade with the rest of the world. In the initial steady state, these trade flows are calibrated to match those implied by Statistics Canada's IO table-consistent inter-provincial and international trade data. In our baseline model, during downturns we allow any shortfalls in required inputs that cannot be produced locally to be imported either from other provinces or other countries. This assumption greatly simplifies the analysis by allowing us to ignore inter-regional equilibrium conditions and is also consistent with the short-term assumption that goods/services prices are fixed. It

⁶Because of its short-term, intra-year nature we must also allow for seasonal fluctuations (see below).

⁷The lack of price adjustment assumed here results in unemployment without micro-founding the underlying frictions giving rise to it. Such a situation may, in part, result from explicit policies to outlaw perceived "price-gouging."

is possible, however, to consider scenarios in which imports of some required inputs are constrained.

2.3. **Seasonality.** As noted above, in considering short-term (intra-year) dynamics, it is important to allow for seasonal variation which plays a significant role in most industries. Such seasonality is incorporated into the model so that results are reported relative to the seasonal norm that would have been predicted in each month in the absence of the pandemic. We compute this counterfactual, "normal" scenario by first calculating the share of total annual hours worked in industry *i* attributed each month, averaged over the past five years, $s_i(m)$, $m \in \{1, 2, ..., 12\}$. We then multiply aggregate hours worked in each industry in February 2020 by the ratio of this share in each subsequent month to that in February 2020 in order to obtain a predicted counterfactual series for aggregate hours.

To compute a similar counterfactual prediction for industry GDP, we feed the counterfactual hours into the model and combine the resulting share of annual GDP attributed to each month with a pre-COVID forecast of GDP in each industry and location for 2020.⁸ This approach to adjusting for seasonality cannot fully account for production processes that inherently take place over time according to a seasonal pattern. If GDP is estimated using sales of gross output, the timing may be significantly different from the allocation of hours in production. For example, in the agricultural sector planting of crops might require an increase in hours in May but the associated sales do not occur until after harvest. We discuss further the limitations and conceptual challenges presented by these issues in the conclusion.

2.4. **Recovery dynamics.** Denote the maximum hours expected to be used in production in period *t*, in the absence of lock-down restrictions, as $\bar{H}_i^*(t)$.⁹ Once labour market restrictions are relaxed in sector *i*, we assume the actual upper bound on total hours evolves according to

$$\bar{H}_{i}(t) = (1 - e^{-\lambda_{i}(t-r_{i})})\bar{H}_{i}^{*}(t) + e^{-\lambda_{i}(t-r_{i})}\bar{H}_{i}(r_{i}), \ \forall t \ge r_{i}$$
(2)

where r_i denotes the reopening date for sector *i* and λ_i denotes the maximum rate at which industry *i* can expand hours of employment once the lock-down is lifted. Actual aggregate hours are thus bounded above by this maximum, $H_i(t) \leq \bar{H}_i(t)$.

Although the production side of the model is expressed in terms of aggregate labour hours, the household demand specification requires an estimate of aggregate employment. A feature of the lock-down was that both employment and average hours per

⁸Forecasts come from the Conference Board of Canada's Provincial Outlook Long-Term Economic Forecast for 2020.

⁹Note that these "normal" hours are time-varying due to seasonal fluctuations in each industry.

worker fall significantly. As the economy recovers, firms are able to adjust aggregate hours along both margins. We develop a reduced-form model of employment adjustment as the need for aggregate hours expands. Specifically, we assume that as long as the implied level of average hours is below the pre-COVID norm for that month, firms increase employment towards its pre-COVID norm only sluggishly. This is intended to reflect the idea that it is relatively costly to hire new workers rather than expanding the hours of existing workers and that firms may be hesitant to commit to new employment in the face of demand uncertainties. Once normal average hours have been obtained, employment is assumed to adjust in proportion to aggregate hours.

We thus model employment as evolving according to:

$$L_i(t) = \min\{\hat{L}_i(t), H_i(t)/h_i^*(t)\}.$$
(3)

where $h_i^*(t)$ denotes normal average hours in industry *i* at time *t*, and

$$\hat{L}_i(t) = L_i(t-1)^{\alpha_i} L_i^*(t)^{1-\alpha_i}.$$
(4)

Here the parameter $\alpha_i \in (0, 1)$ reflects the "sluggishness" of employment adjustment in industry *i*. While this reduced form set up is admittedly crude, it captures the spirit of structural employment models featuring adjustment costs and hiring/firing frictions.¹⁰

2.5. **Parameterization.** Symmetric Provincial I-O Summary Tables, inter-provincial and international trade flow data and labour market data (wages and employment) for each province are provided by Statistics Canada.¹¹ These annual data were used to calibrate the parameters of the model and the specific IO structure of each provincial economy. This core structure consists of 32 "summary" industries for each province.¹² However, since the LFS data is reported at a higher level, we aggregated the underlying results to 16 industries.

The provincial I-O tables are based on annual Supply-Use production data for 2015. While we maintain the same proportional production structure, we artificially "grow" output and final demands in each sector and province in proportion to observed industry GDP growth between 2015 and 2019. Thus, initial industry labour productivity (output per hour worked) in the model reflects that in 2019. The annual input-output matrix is

¹⁰E.g. Hamermesh and Pfann, 1996; Cooper, Haltiwanger and Willis, 2015.

¹¹Date sources: Statistics Canada Tables 15-211-X, "Provincial Symmetric Input-Output Tables"; Statistics Canada Table 14-10-0043-01, "Average usual and actual hours worked in a reference week by type of work" ¹²The more detailed national supply-use tables are used by Statistics Canada to estimate monthly industry GDP but only at the national level and with a significant lag.

assumed to apply to monthly production, so that seasonal-adjustments come through the impact of changes in hours worked only.¹³

Initial constraints on aggregate hours during the lock-down in March and April 2020 were calibrated so that the implied hours worked in each sector closely match those in the monthly LFS for each province.¹⁴ After May 2020, as restrictions started to be relaxed in various sectors, the upper bound on hours follows the recovery dynamics described above. Post lock-down recovery speeds by sector, λ_i , were calibrated to match the fraction of businesses indicating they would be able to recover within one month according to a recent Statistic Canada business survey.¹⁵ This effectively assumes that recovery rates are independent of the size of businesses within each sector. This estimate by industry is only available on average for Canada and not by province.

"Other income" is set equal to 28% of total employment compensation based on figures from the Ontario Ministry of Finance.¹⁶ The monthly income while unemployed is set equal to b = \$2000 which is equal to the Canadian Emergency Response Benefit (CERB). Inventory depreciation rates, δ_i , are set equal to 0.99 for all service sectors and 0.01 for all goods producing sectors. That is, there are basically no inventories of services carried between periods, while goods inventories are assumed to lose little value over a month. We follow Avelino and Hewings (2019) in setting the expectations adjustment parameter to $\sigma = 0.05$. These values are somewhat arbitrary, but the results are not very sensitive to similar alternative values. Finally, based on experimentation during the early months of the pandemic, the employment adjustment parameter was set to $\alpha_i = 0.9 \ \forall i$. This value generated reasonable one month-ahead predictions for employment through June and our main results are not highly sensitive to it.

2.6. **Recovery Scenarios.** The extent of the impact of the lock-down and timing of reopening for each industry in each province reflects both the observed LFS data and our reading of the various recovery plans for each province. While the details and exact timing of these plans vary across provinces, there are many commonalities. For example, most provinces have followed a three-stage re-opening plan that started some time in May and by mid-August they had all reached the third stage. A few provinces started their first stage prior to the May LFS reference week, whereas most others started later. Some provinces identify more than 3 phases in their plans but since they occurred in

¹³Avelino (2017) discusses methods for adjusting the I-O matrix itself to allow for temporal disaggregation. Unfortunately, Statistics Canada does not provide the seasonally-unadjusted provincial industry GDP data on a monthly basis that would be required to apply these methods.

¹⁴Statistics Canada Table 14-10-0022-01, "Labour force characteristics by industry, monthly, unadjusted for seasonality."

¹⁵Statistics Canada Table 33-10-0244-01, "Length of time business require before being able to resume normal operations once social distancing measures are removed, by business characteristic."

¹⁶https://www.fin.gov.on.ca/en/economy/ecaccts/ecat11.html

fairly rapid succession between LFS reference weeks, we have effectively combined some of them. We calibrated the timing and extent of the maximum hours in each industry to generate hours-worked predictions matching as closely as possible those observed to date.¹⁷

It is possible to introduce multiple demand-side shocks into the model. In principle, these could come from any component of aggregate expenditure. Although overall household consumption expenditure is an endogenous function of income in the model, the propensity to consume out of current income and expenditure shares on different items are exogenous and could also be subject to shocks. We present a baseline scenario that assumes that consumer expenditure patterns and maximum hours will return to their pre-COVID patterns, as well as a series of alternative scenarios that incorporate several potential demand shocks that are likely to impact the Canadian economy going forward.

- **Baseline Recovery Scenario:** For most provinces, our baseline recovery scenario consists of an "Optimistic Staged recovery", in which each stage occurs between successive LFS reference weeks: Stage 1 between mid-May and mid-June, Stage 2 between mid-June and mid-July and stage 3 between mid-July and mid-August.
- Dr. Doom Scenario: Although households are not forward-looking in our model, we replicate the qualitative implications of a decline in expected wealth by assuming that household's propensity to consume out of current income, Φ(t), declines by 20% across the board by May 2020 and subsequently recovers only gradually. Other elements of this scenario are the same as the baseline.
- Kill Fun Scenario: While the lock-down itself constrains production, in some sectors it seems likely that demand will remain lower for some time to come. In this scenario we assume a persistent 50% decline in the demand for Accommodation and Food Services and Arts and Recreation. Other elements of this scenario are the same as the baseline.
- End of Tourism Scenario: One of the most significant impacts of COVID-19 have been restrictions on international travel and tourism. In this scenario we assume that, in addition to the declines in domestic demand, export demand for Food/Accommodation, Arts/Recreation services and Transport services each decline by 50%.

Finally, we formulate a fifth scenario that represents a further lock-down in the fall of 2020 resulting from a second wave in the pandemic. Such a second wave appears to

¹⁷Recovery plan websites for each province are given in Appendix 3. Quebec's recovery plan does not explicitly identify any stages but their actual behaviour follows a similar pattern to other provinces, albeit at a different pace.

be viewed by epidemiologists as highly likely following the opening up of most sectors through the summer and the restart of schools and universities in September:

• Second Wave Scenario: Following the ramp up of confirm cases through September and early October, provinces impose a second lock-down in mid-October. Labour market restrictions and re-opening paths are assumed to evolve in the same way as during the first wave.

The COVID-19 pandemic has undoubtedly been the single dominant factor impacting the Canadian economy during 2020. However, it is not the only major global shock that has occurred. While our counterfactual prediction attempts to adjust for "normal" seasonal movements, it does not control for other such shocks that were not predicted prior to 2020. In particular, a major shock that significantly impacted several provinces at the beginning of 2020 was the global oil production glut due to a disagreement on production levels between Russia and Saudi Arabia and the consequent decline in oil prices. Since it is likely that the pandemic also contributed significantly to the glut and this price decline, it is unclear how much of the downturn in the oil sector should be attributed to each cause. For this reason we report our scenario results below excluding the aggregate sector containing oil production. The results for all sectors including oil production are reported in Appendix 2.

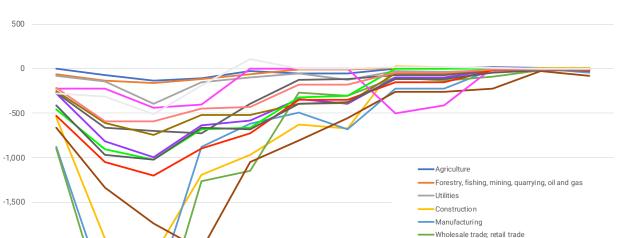
3. Results

We begin by reporting results from our optimistic scenario, which assumes that reopening continues as planned across the provinces, and that the economy eventually returns to levels of pre-COVID activity. Then, we explore how projections change under alternative predictions about how COVID-19 may change consumer behavior and possibility of a second wave lock-down.

3.1. **The Baseline Optimistic Scenario.** To illustrate the nature of the results, Figure 1 depicts the dynamic evolution of the deviation of GDP from its seasonal norm for each sector that is implied by the Optimistic Staged Recovery scenario for Ontario, Canada's largest province economically.¹⁸ The model is run for a 12 month period from March 2020 to February 2021. Estimates up to July reflect a calibration of the maximum hours to match as closely as possible observed actual hours worked, while subsequent values reflect the assumptions of the optimistic staged recovery scenario.

While the Food and Accommodation services was proportionally the worst hit sector, in terms of lost GDP, the Wholesale and Retail trade and Manufacturing sectors were impacted the most. The impact on total hours in the Finance/Real Estate sector was

 $[\]overline{}^{18}$ All amounts are measured in current 2020:Q1 Canadian dollars.



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FIGURE 1. Impact on GDP Relative to Counterfactual by Sector in Ontario in the Optimistic Scenario (in millions of CAD)

September

October

August

relatively low but the resulting impact on GDP in that sector has been much larger and persistent. Going forward, even the optimistic scenario predicts significant deviations from seasonal norms until the end of year. The rate of recovery of each sector during the reopening depend on both the maximum feasible hours in that sector and the rates of recovery occurring in other sectors.

Although we do not have the space here to present similar graphs for all the provinces, there is quite a bit of heterogeneity in the industry GDP impacts across them.¹⁹ For example, the estimated losses in GDP coming from the Finance/Real Estate and Construction sectors were the largest in British Columbia, whereas Manufacturing took the biggest GDP hit in Quebec. While many of the losses in April and May were more pronounced in Quebec than in other provinces, the more rapid opening up resulted in less persistence.

Table 1 documents the monthly estimated proportional impacts on aggregate GDP for each province under this Optimistic scenario. Table 2 shows the aggregate impact on hours. As before, these estimates are relative to the seasonal norm that we estimate

-2.000

-2,500

-3.000

-3.500

March

April

Mav

June

Julv

Transportation and warehousing

Accommodation and food services
 Other services (except public administration)

Educational services Health care and social assistance Information, culture and recreation

Public administration

November December

Finance, insurance, real estate, rental and leasing
 Professional, scientific and technical services
 Business, building and other support services

January

February

¹⁹Please contact the authors for these results.

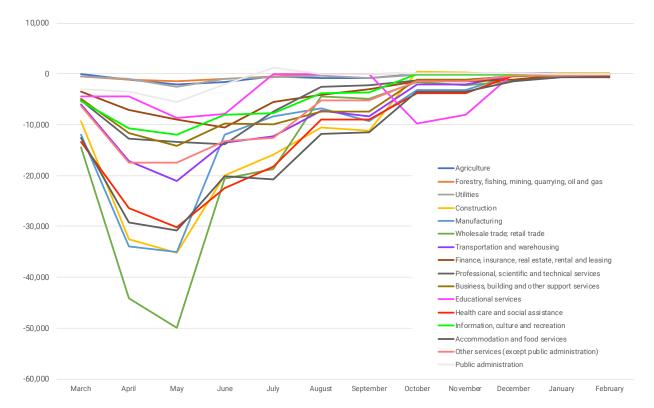


FIGURE 2. Impact on Hours Relative to Counterfactual by Sector in Ontario in the Optimistic Scenario (in thousands)

TABLE 1. % Impact on GDP Relative to Counterfactual by Province in the Optimistic Scenario (excluding "Forestry, fishing, mining, quarrying, oil and gas")

	Mar.	Apr.	May	June	July	Aug.	Sept.	Oct.	Nov.	Dec.	Jan.	Feb.	Year (%)	Year (\$M)
AB	-5.4%	-23.4%	-25.5%	-15.0%	-8.1%	-5.3%	-5.6%	-3.2%	-2.9%	-1.8%	-0.3%	-0.3%	-8.0%	-22,488
BC	-8.4%	-24.0%	-25.8%	-18.7%	-13.0%	-7.9%	-8.0%	-3.0%	-2.8%	-1.8%	-0.6%	-0.4%	-9.4%	-25,514
MB	-3.1%	-16.2%	-19.9%	-14.3%	-6.9%	-4.4%	-4.6%	-2.2%	-1.9%	-0.8%	0.1%	-0.1%	-6.2%	-4,245
NB	-7.0%	-20.6%	-21.9%	-11.9%	-5.3%	-4.8%	-5.1%	-2.5%	-1.8%	-0.8%	-0.1%	-0.2%	-6.7%	-2,240
NL	-8.7%	-31.4%	-34.0%	-15.0%	-7.3%	-4.8%	-5.3%	-1.9%	-0.7%	0.8%	0.2%	0.1%	-8.6%	-1,945
NS	-8.8%	-21.3%	-25.3%	-19.5%	-11.7%	-7.5%	-7.4%	-1.9%	-1.7%	-0.7%	0.0%	-0.3%	-8.7%	-3,429
ON	-9.3%	-24.3%	-27.5%	-15.9%	-11.7%	-6.7%	-6.8%	-2.5%	-2.5%	-0.7%	-0.2%	-0.4%	-8.8%	-69,817
PE	-10.5%	-25.5%	-28.2%	-17.4%	-9.3%	-8.5%	-8.0%	-1.6%	-0.9%	0.4%	0.4%	-0.1%	-8.9%	-575
QC	-10.3%	-34.4%	-38.5%	-13.2%	-5.7%	-2.9%	-2.7%	-3.7%	-3.8%	-1.0%	-0.7%	-0.7%	-9.4%	-37,981
SK	-2.7%	-19.7%	-23.9%	-16.1%	-5.7%	-3.4%	-4.1%	-1.2%	-0.4%	0.1%	0.3%	0.1%	-6.4%	-4,308
Canada	-8.4%	-25.7%	-28.7%	-15.5%	-9.6%	-5.7%	-5.8%	-2.8%	-2.7%	-1.0%	-0.3%	-0.4%	-8.7%	-172,542

would have been expected in the absence of COVID-19.²⁰ Note first, the impacts on hours worked is generally proportionally greater than that on GDP. The implied increase in labour productivity is really the result of a composition effect: low value sectors, such

²⁰Using proportional impacts rather than levels is more meaningful for comparing across these very heterogeneous regions.

as Accommodation and Food Services, experienced much larger % reductions in hours worked in comparison to high value sectors, such as Financial Services.

TABLE 2. % Impact on Hours Relative to Counterfactual by Province in the Optimistic Scenario (excluding "Forestry, fishing, mining, quarrying, oil and gas")

	Mar.	Apr.	May	June	July	Aug.	Sept.	Oct.	Nov.	Dec.	Jan.	Feb.	Year (%)	Year (1,000s)
AB	-7.4%	-27.5%	-29.8%	-16.8%	-10.0%	-6.2%	-6.5%	-3.8%	-3.5%	-2.0%	-0.3%	-0.3%	-9.4%	-314,957
BC	-9.5%	-27.0%	-28.9%	-20.0%	-14.9%	-8.7%	-8.6%	-3.4%	-3.1%	-1.8%	-0.5%	-0.3%	-10.4%	-388,081
MB	-4.5%	-20.7%	-24.5%	-15.3%	-7.8%	-5.3%	-5.4%	-2.5%	-2.1%	-0.9%	0.1%	-0.1%	-7.4%	-74,044
NB	-8.4%	-25.0%	-26.2%	-12.2%	-5.8%	-4.6%	-5.1%	-2.3%	-1.4%	-0.4%	0.0%	0.0%	-7.4%	-40,573
NL	-8.7%	-33.3%	-36.8%	-17.1%	-9.1%	-5.5%	-5.9%	-2.3%	-1.7%	-0.1%	0.2%	0.0%	-9.6%	-30,330
NS	-10.4%	-26.2%	-30.4%	-19.8%	-13.4%	-9.1%	-9.0%	-1.6%	-1.4%	-0.5%	-0.1%	-0.1%	-9.9%	-69,512
ON	-11.0%	-29.4%	-32.3%	-18.0%	-14.5%	-7.8%	-8.1%	-3.1%	-3.0%	-0.6%	-0.2%	-0.4%	-10.4%	-1,175,893
PE	-10.3%	-28.1%	-31.3%	-19.2%	-10.5%	-9.3%	-9.1%	-1.1%	-0.8%	0.4%	0.5%	0.2%	-9.6%	-12,070
QC	-11.8%	-39.3%	-43.4%	-13.8%	-7.7%	-3.3%	-3.0%	-3.1%	-3.1%	-0.6%	-0.3%	-0.4%	-10.2%	-644,956
SK	-3.8%	-24.8%	-27.7%	-17.2%	-6.7%	-4.1%	-4.7%	-1.9%	-1.2%	-0.3%	0.2%	-0.1%	-7.6%	-65,868
Canada	-10.0%	-30.4%	-33.3%	-17.0%	-11.8%	-6.5%	-6.6%	-3.1%	-2.9%	-0.9%	-0.3%	-0.3%	-10.0%	-2,816,285

Comparing across provinces (excluding the sector containing oil production), Quebec and British Columbia are expected to experience the largest % loss of GDP over the 12 month period, while Manitoba experienced the least. As may be seen, while the impacts on Quebec are estimated to have been the largest during April and May, its more rapid re-opening is forecast, in this scenario, to result in much less persistent losses during the summer. Ontario's overall % GDP loss emerges as being similar to Canada as a whole. Overall, the estimated GDP loss for all the provinces combined between March 2020 and February 2021 under the optimistic scenario amount to just over \$170 billion.

3.2. **Other Scenarios.** As an example, Figure 3 illustrates the monthly aggregate GDP impacts of each of the five scenarios described above, for Ontario. The demand shocks for each scenario were assumed to all start impacting the economy by June. Not surprisingly, since these scenarios either introduce negative demand shocks or further negative supply shocks, they result in greater losses across the board than the Optimistic scenario. Of those that introduce demand shocks, the Dr. Doom scenario implies the largest and most persistent losses. Even though the % reduction in the marginal propensity to consume is relatively small and not permanent, it is more widespread across sectors.

The most dramatic impact comes from the Second Wave scenario. This scenario is somewhat literal in that it replicates the lock-down measures and re-opening paths followed during the first wave. The fact that the GDP impacts are quantitatively different largely reflects the seasonal variation in the counterfactual. For example, overall economic activity in December usually contributes a relatively large share of annual GDP, so the loss due to a lock-down would be relatively large. One would hope, of course, that lessons learned and adaptation in production modes would result in less strict measures and smaller GDP impacts.

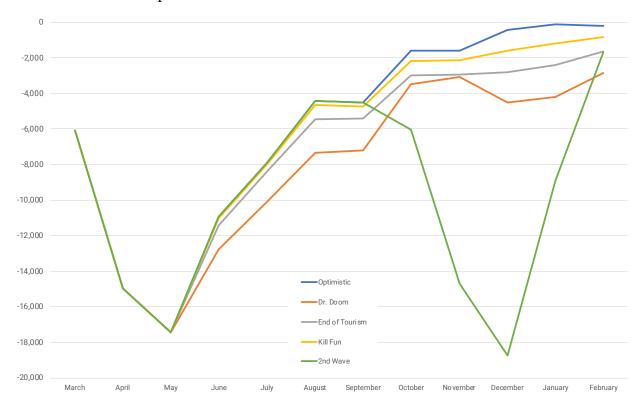


FIGURE 3. Impact on GDP Relative to Counterfactual by Scenario in Ontario (in millions of CAD)

Tables 3 and 4 compare the overall annual aggregate losses in each scenario across the provinces in terms of GDP and hours worked, respectively. The impacts of the various demand changes through time depend on the shares of the relevant sectors in each province and the importance of consumption by residents in overall final demand. For example, the three "demand-shock" scenarios all result in British Columbia experiencing the worst losses in large part due to the relative size of its Accommodation/Food and Recreations sectors and the impact that a persistent decline in the propensity to consume this has on its Financial/Real Estate sector. The Dr. Doom scenario results in overall GDP losses for all the provinces exceeding \$230 billion.

A second wave scenario in the fall, that looks like the first, would impact PEI, Newfoundland and Quebec most severely relative to seasonal norms. As a result, these provinces would experience the largest proportional GDP losses over the 12 month period. If Manitoba can achieve similar success in avoiding and mitigating the transmission of the virus, our estimates suggest that it will continue to be impacted the least. According to these scenario estimates, the overall GDP loss due to combined first and second waves and consequent lock-downs would exceed \$285 billion over the year.

TABLE 3. Impact on GDP Relative to Counterfactual by Province in All Scenarios (excluding "Forestry, fishing, mining, quarrying, oil and gas")

	Optimistic		Dr. 1	Doom	End of	Tourism	Kil	l Fun	2nd	Wave
	%	\$M	%	\$M	%	\$M	%	\$M	%	\$M
AB	-8.0%	-22,488	-10.9%	-30,541	-10.9%	-30,568	-8.7%	-24,601	-12.8%	-35,839
BC	-9.4%	-25,514	-12.7%	-34,265	-12.8%	-34,505	-10.3%	-27,707	-15.1%	-39,760
MB	-6.2%	-4,245	-8.9%	-6,110	-9.2%	-6,313	-6.8%	-4,659	-10.4%	-7,023
NB	-6.7%	-2,240	-10.1%	-3,334	-9.6%	-3,181	-7.2%	-2,396	-12.0%	-3,924
NL	-8.6%	-1,945	-12.4%	-2,787	-10.8%	-2,423	-9.4%	-2,121	-16.5%	-3,631
NS	-8.7%	-3,429	-12.3%	-4,830	-10.5%	-4,140	-9.1%	-3,589	-15.9%	-5,971
ON	-8.8%	-69,817	-11.9%	-93,603	-10.3%	-81,476	-9.4%	-74,386	-15.1%	-115,623
PE	-8.9%	-575	-11.9%	-765	-10.9%	-706	-9.2%	-596	-18.2%	-1,109
QC	-9.4%	-37,981	-12.5%	-50,379	-11.2%	-45,216	-10.1%	-40,724	-16.2%	-64,754
SK	-6.4%	-4,308	-9.4%	-6,300	-9.1%	-6,125	-7.0%	-4,691	-12.0%	-7,919
Canada	-8.7%	-172,542	-11.8%	-232,915	-10.8%	-214,652	-9.4%	-185,470	-14.7%	-285,554

TABLE 4. Impact on Hours Relative to Counterfactual by Province in All Scenarios (excluding "Forestry, fishing, mining, quarrying, oil and gas")

	Opt	imistic	Dr.	Doom	End of	f Tourism	Ki	ll Fun	2nd	2nd Wave	
	%	1,000s									
AB	-9.4%	-314,957	-11.2%	-374,309	-13.0%	-434,174	-10.5%	-352,841	-15.1%	-502,843	
BC	-10.4%	-388,081	-12.5%	-466,389	-14.4%	-534,317	-11.6%	-432,756	-16.6%	-605,623	
MB	-7.4%	-74,044	-9.1%	-91,026	-11.5%	-114,566	-8.5%	-85,455	-12.5%	-123,847	
NB	-7.4%	-40,573	-9.9%	-53,971	-11.3%	-61,127	-8.3%	-45,407	-13.8%	-73,983	
NL	-9.6%	-30,330	-12.2%	-38,374	-13.1%	-41,217	-11.1%	-35,005	-17.7%	-54,750	
NS	-9.9%	-69,512	-12.3%	-85,963	-12.9%	-90,223	-10.8%	-75,517	-18.4%	-121,837	
ON	-10.4%	-1,175,893	-12.4%	-1,403,346	-12.5%	-1,414,864	-11.2%	-1,272,009	-17.9%	-1,967,841	
PE	-9.6%	-12,070	-11.6%	-14,592	-12.2%	-15,245	-10.0%	-12,543	-20.1%	-23,668	
QC	-10.2%	-644,956	-12.7%	-799,086	-13.0%	-813,115	-11.3%	-712,877	-18.2%	-1,125,728	
SK	-7.6%	-65,868	-9.7%	-83,394	-10.8%	-92,959	-8.7%	-74,910	-14.0%	-117,791	
Canada	-10.0%	-2,816,285	-12.1%	-3,410,451	-12.8%	-3,611,808	-11.0%	-3,099,320	-17.1%	-4,717,910	

4. Concluding Remarks

Our objective in this paper has been to develop and assess a framework to estimate the current and possible future impacts of the COVID-19 pandemic on Canadian provinces, using data that is available with a relatively short time lag. Such a framework can help guide policy when policymakers need weigh very costly trade-offs while responding quickly in times of crisis. The framework needs to be flexible enough to allow consideration of multiple alternative scenarios in a context of low and evolving information regarding the distribution of possibilities. To this end, we have adapted a dynamic input-output model with labour supply constraints, endogenous consumption behaviour and seasonal variation. The flexibility of the model to forecast regional economic outcomes over alternative recovery scenarios makes it a useful tool for policymakers considering different recovery policies.

There are, of course, several limitations to our approach and numerous challenges remain. As noted previously, inherent issues of time-disaggregation generate a number QUANTIFYING THE ECONOMIC IMPACTS OF COVID-19 POLICY RESPONSES

of questions for some sectors. We have effectively treated all seasonal variation as being driven by available labour hours whereas some clearly arises from the demand side and the production function itself likely varies within the year (see Avelino, 2017). A related issue arises in the measurement of industry GDP on a monthly basis inferred via estimates of gross output versus hours or employment. In their national estimates of monthly GDP, Statistics Canada uses a combination of estimates from different sources (e.g. gross output or sales from the Monthly Survey of Manufacturing and person-hours or employment from the Survey of Payroll Employment and Hours). In some sectors, which approach is used likely makes little difference, but in others, the timing may matter. For example, aggregating to the national level, our estimates of GDP growth for manufacturing and Food/Accommodation services for March through May are very similar to those of Statistics Canada. For agriculture, however, the timing of production in our model is likely rather different from the timing of sales in the data.²¹

The production relationships in the model are quite simple and assume strong complementarity. While we have argued that the degree of substitution between inputs is likely limited in the short run, a more general framework (for example, involving nested CES functions) could potentially provide more accurate forecasts over time. A significant challenge to implementing such a generalization is the parameterization of the various elasticities of substitution that would arise.²² Likewise, many other features of the model that have been treated in a reduced-form fashion here could be based on more appealing micro-foundations. In doing so, formulating the choices of households and managers in a forward-looking fashion could enhance the framework's usefulness, especially for normative considerations.

Finally, in this paper we have not integrated any epidemiological features into the model. However, the likelihood and nature of future restrictions will depend on interactions between economic activity and disease transmission rates. Recently, Baqaee et al. (2020) have developed a framework in which age-specific transmission rates reflect the impact of economic activity across industrial sectors in the US economy. However, their model assumes a high degree of substitutability across sectors and does not make implicit the dynamic input-output structure of the economy. As they note: "complementarities in consumption and in production can amplify real GDP losses, relative to what we have reported, by somewhere between 10% and 40%." In related work, we are working on combining state-of-the art epidemiological modelling with the STUDIO model to develop an integrated framework.

²¹Nevertheless the implied contractions in overall national GDP during the first and second quarters of 2020 were very close to those estimated by Statistics Canada.

²²Moreover, price and wage rigidities would need to be micro-founded to be consistent with the observed declines in employment.

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Appendix 1: Model Details

This appendix lays out a variant of the Generalized Dynamic Input Output (GDIO) model of Avelino and Hewings (2019), which we refer to as the Short-Term Undercapacity Dynamic Input-Output (STUDIO) model. The fact that the economy is operating below capacity in the short term implies that the capital stock available to each sector is assumed not to be a constraint on production. However, the hours available for use in production in sector j, $H_j(t)$, is assumed to be subject to a time-varying upper bound, $\bar{H}_j(t)$.²³ During normal times, this upper bound reflects the available labour supply to each industry at each point of time. During a lock-down, it reflects policy decisions and health restrictions and during a reopening it reflects the capacities of industries to expand while ensuring the health and safety of its workers.

4.1. **Allocation of Current Production.** The maximum potential output that can be produced at time *t* by sector *j* is given by the Leontief production function

$$\bar{Q}_{j}(t) = \min\left[\frac{\bar{z}_{1j}(t)}{A_{1j}}, \frac{\bar{z}_{2j}(t)}{A_{2j}}, ..., \frac{\bar{z}_{Nj}(t)}{A_{Nj}}, \frac{\bar{H}_{j}(t)}{A_{Hj}}\right],$$
(5)

where $\bar{z}_{ij}(t)$ denotes the quantity of inputs produced by sector *i* in the previous period that are available for use in sector *j*, A_{ij} is the unit input requirement of input *i* in sector *j* and A_{Hj} is the unit input requirement for labour hours. The *actual* output produced by sector *j* is the lesser of $\bar{Q}_j(t)$ and a *scheduled* output level that was determined in the previous period, net of any inventories of intermediate inputs that were unused from the previous period:

$$X_{j}^{A}(t) = \min\left[\bar{Q}_{j}(t), \ X_{j}^{S}(t) - I_{j}^{I}(t-1)\right]$$
(6)

²³Such a constraint on factors of production distinguishes the model from standard static IO models and imply that multiplier effects are limited, as in a CGE model.

The stock of materials and supplies produced by sector i for use in sector j that remain unused at the end of period t is given by

$$\Phi_{ij}(t) = \max\left[\bar{z}_{ij}(t) - A_{ij}X_j^A(t), 0\right]$$
(7)

Since prices are assumed fixed in the short-run, rationing is required whenever the actual output produced at *t* falls below that previously scheduled. Here, we assume a uniform rationing rule such that all users of output produced by sector *i* receive the same fraction of the output produced:

$$r_i(t) = X_i^A(t) / X_i^S(t)$$
(8)

Total hours actually worked in sector *i* is given by

$$H_i(t) = A_{Hi} X_i^A(t).$$
(9)

Total final demand for goods and services from industry *i* is then given by

$$Y_i^T(t) = Y_i^C(t) + Y_i^X(t) + Y_i^O(t)$$
(10)

where $Y_i^C(t)$ denotes final consumption demand, $Y_i^X(t)$ denotes final export demand and $Y_i^O(t)$ denotes other final demand (investment expenditures and government consumption). Final consumption demand is given by a potentially time-varying share, $s_i(t)$, of overall consumption:

$$Y_i^{\mathcal{C}}(t) = s_i(t)\mathcal{C}(t). \tag{11}$$

The actual vector of final demand supplied locally is the lesser of total final demand and the fraction of scheduled final demand that is produced plus any inventories of final goods carried over from the previous period

$$Y_{i}^{A}(t) = \min\left[Y_{i}^{T}(t), \ Y_{i}^{S}(t) \times r_{i}(t) + I_{i}^{F}(t-1)\right]$$
(12)

If there are no constraints on trade, any shortfall in final demand is imported

$$M_{i}^{F}(t) = Y_{i}^{T}(t) - Y_{i}^{A}(t)$$
(13)

The stock of inventories of finished goods for final demand that will be carried over to the subsequent period are given by the excess supply of output for final demand:

$$I_i^F(t) = (1 - \delta_i) \max\left[r_i(t)Y_i^S(t) - Y_i^A(t) + I_i^F(t - 1), 0\right]$$
(14)

4.2. **Production Planning and Purchasing of inputs for next period.** Managers are assumed to form an expectation of the final demand for each sector *i* in the next period. We assume this is given by revising up or down the current total final demand by an amount proportional to the current shortfall in final demand:

$$Y_{i}^{E}(t+1) = Y_{i}^{T}(t) + \sigma \left(Y_{i}^{T}(t) - Y_{i}^{A}(t)\right)$$
(15)

Managers must then form an estimate of how much output will be required to meet this expected final demand for next period plus the vector of inputs required for the period after that. This calculation is simplified by assuming that the output estimate is equal to that which would be necessary to produce the expected final demand vector in steady state.²⁴ This is given by applying the Leontief inverse to the vector of expected final demands over and above any inventories of final goods carried forward:

$$\mathbf{X}^{R}(t+1) = (\mathbf{I} - \mathbf{A})^{-1} \left(\mathbf{Y}^{E}(t+1) - \mathbf{I}^{F}(t) \right)$$
(16)

Taking account of labour supply constraints, the constrained required output of good j going forward is

$$X_j^R(t+1) = \min\left[\mathbf{X}_j^R(t+1), \ \frac{\bar{H}_j(t)}{A_{Hj}}\right]$$
(17)

This vector of required output implies a matrix of intermediate input requirements that will be needed over and above any materials and supplies carried forward from the current period:

$$z_{ij}^{R}(t+1) = \max\left[A_{ij}X_{j}^{R}(t+1) - \Phi_{ij}(t), 0\right]$$
(18)

The matrix of inputs actually purchased locally for use in the next period is then given by the lesser of that required and the rationed fraction of the levels scheduled previously plus any inventories of finished intermediates carried over:

$$z_{ij}^{A}(t+1) = \min\left[z_{ij}^{R}(t+1), \ z_{ij}^{S}(t) \times r_{i}(t) + I_{i}^{I}(t-1) \times d_{ij}(t)\right]$$
(19)

Here, d_{ij} represents an inventory distribution scheme needed to allocate inventories of good *i* to production of good *j*. We assume that inventories are allocated only to sectors in which there is an excess input requirement, in proportion to the allocation of scheduled output. That is

$$d_{ij}(t) = \frac{\chi_{ij} \times z_{ij}^{S}(t) \times r_{i}(t)}{\sum_{j} \chi_{ij} \times z_{ij}^{S}(t) \times r_{i}(t)}$$
(20)

where

$$\chi_{ij} = \begin{cases} 1, & \text{if } z_{ij}^R(t+1) > z_{ij}^S(t) \times r_i(t) \\ 0, & \text{otherwise} \end{cases}$$
(21)

In this small open economy, it is assumed that any difference between the required inputs and those that can be produced locally will be imported:

$$M_{ij}^{I}(t+1) = z_{ij}^{R}(t+1) - z_{ij}^{A}(t+1)$$
(22)

²⁴In general this is a complicated problem because of the asynchronous nature of input production and use. Formulating this problem as a dynamic programming problem with rational expectations might be feasible but, given the context, we have little information on the distribution of possible incomes.

Inventories of finished goods for intermediate demand carried into the next period are given by

$$I_i^I(t) = (1 - \delta_i) \max\left[\sum_j z_{ij}^S(t) r_i(t) + I_i^I(t - 1) - \sum_j z_{ij}^A(t + 1), 0\right]$$
(23)

where δ_i denotes the depreciation rate of inventories in sector *i*. The total available quantity of inputs produced in sector *i* that are available for use in sector *j* next period is then given by

$$\bar{z}_{ij}(t+1) = z_{ij}^A(t+1) + M_{ij}^I(t+1) + \Phi_{ij}(t)$$
(24)

The scheduled output for the next period is

$$X_{j}^{S}(t+1) = \min\left[\frac{\bar{z}_{1j}(t+1)}{A_{1j}}, \frac{\bar{z}_{2j}(t+1)}{A_{2j}}, ..., \frac{\bar{z}_{Nj}(t+1)}{A_{Nj}}, \frac{\bar{H}_{j}(t)}{A_{Hj}}\right]$$
(25)

and the scheduled inputs to be produced locally are

$$z_{ij}^{\mathcal{S}}(t+1) = RPC_{ij} \times A_{ij} \times X_j^{\mathcal{S}}(t+1),$$
(26)

where RPC_{ij} denotes the regional purchase coefficient for input *i* in the production of good *j*. The scheduled final demand vector for next period is then

$$Y_i^S(t+1) = \min\left[Y_i^E(t+1), \ X_i^S(t+1) - \sum_j z_{ij}^S(t+1) + I_i^F(t)\right]$$
(27)

5. Appendix 2: Results for all Sectors

TABLE 5. % Impact on GDP Relative to Counterfactual by Province in theOptimistic Scenario (All Sectors)

	Mar.	Apr.	May	June	July	Aug.	Sept.	Oct.	Nov.	Dec.	Jan.	Feb.	Year (%)	Year (\$M)
AB	-4.0%	-20.3%	-22.0%	-13.8%	-6.1%	-3.8%	-4.1%	-3.0%	-2.8%	-1.5%	-0.2%	-0.2%	-6.8%	-25,978
BC	-8.0%	-22.7%	-24.5%	-17.7%	-12.2%	-7.5%	-7.4%	-2.7%	-2.5%	-1.6%	-0.6%	-0.3%	-8.9%	-25,428
MB	-3.3%	-16.9%	-20.5%	-13.8%	-6.2%	-4.3%	-4.5%	-2.0%	-1.8%	-0.7%	0.1%	-0.1%	-6.2%	-4,352
NB	-7.0%	-20.6%	-21.8%	-12.3%	-5.0%	-4.8%	-5.2%	-2.3%	-1.6%	-0.7%	0.0%	-0.1%	-6.7%	-2,283
NL	-11.4%	-35.1%	-42.9%	-14.4%	-6.9%	-9.1%	-8.7%	-2.6%	-0.9%	0.1%	-0.2%	-0.1%	-10.5%	-3,741
NS	-8.8%	-20.9%	-25.3%	-19.6%	-11.1%	-7.3%	-7.3%	-1.6%	-1.4%	-0.5%	0.1%	-0.2%	-8.5%	-3,457
ON	-9.3%	-24.3%	-27.5%	-15.9%	-11.7%	-6.6%	-6.7%	-2.5%	-2.4%	-0.7%	-0.2%	-0.4%	-8.8%	-70,367
PE	-10.6%	-25.9%	-29.0%	-19.2%	-9.1%	-8.8%	-9.6%	-1.1%	-0.7%	0.5%	0.5%	0.0%	-9.2%	-604
QC	-10.3%	-34.6%	-38.7%	-13.3%	-5.6%	-2.8%	-2.7%	-3.6%	-3.6%	-1.0%	-0.6%	-0.7%	-9.4%	-38,878
SK	-5.7%	-24.8%	-28.0%	-21.3%	-9.3%	-3.1%	-4.7%	-1.6%	-1.1%	-0.3%	0.2%	0.1%	-8.1%	-7,477
Canada	-8.0%	-25.1%	-28.1%	-15.4%	-9.1%	-5.4%	-5.5%	-2.8%	-2.6%	-1.0%	-0.3%	-0.3%	-8.4%	-182,564

TABLE 6. % Impact on Hours Relative to Counterfactual by Province in theOptimistic Scenario (All Sectors)

	Mar.	Apr.	May	June	July	Aug.	Sept.	Oct.	Nov.	Dec.	Jan.	Feb.	Year (%)	Year (1,000s)
AB	-6.9%	-26.3%	-28.4%	-16.4%	-9.3%	-5.7%	-6.0%	-3.7%	-3.4%	-1.9%	-0.3%	-0.3%	-8.9%	-324,706
BC	-9.4%	-26.5%	-28.4%	-19.7%	-14.7%	-8.6%	-8.4%	-3.3%	-3.0%	-1.8%	-0.5%	-0.3%	-10.2%	-387,717
MB	-4.5%	-20.9%	-24.6%	-15.2%	-7.6%	-5.3%	-5.4%	-2.5%	-2.1%	-0.9%	0.1%	-0.1%	-7.4%	-74,499
NB	-8.3%	-24.8%	-26.1%	-12.8%	-5.5%	-4.6%	-5.3%	-2.0%	-1.1%	-0.2%	0.1%	0.1%	-7.4%	-41,493
NL	-9.1%	-33.8%	-38.2%	-16.9%	-8.9%	-6.2%	-6.4%	-2.4%	-1.6%	-0.2%	0.1%	0.0%	-9.9%	-33,342
NS	-10.3%	-25.8%	-30.2%	-19.8%	-12.9%	-8.9%	-8.8%	-1.4%	-1.2%	-0.4%	0.0%	-0.1%	-9.8%	-69,952
ON	-11.0%	-29.4%	-32.2%	-18.0%	-14.4%	-7.8%	-8.1%	-3.0%	-3.0%	-0.6%	-0.2%	-0.4%	-10.4%	-1,180,489
PE	-10.4%	-28.6%	-32.1%	-21.2%	-10.3%	-9.6%	-10.8%	-0.6%	-0.6%	0.5%	0.5%	0.2%	-10.0%	-12,693
QC	-11.7%	-39.3%	-43.4%	-13.8%	-7.7%	-3.3%	-3.0%	-3.1%	-3.1%	-0.6%	-0.3%	-0.4%	-10.2%	-651,315
SK	-4.2%	-25.4%	-28.2%	-18.0%	-7.3%	-4.0%	-4.8%	-2.0%	-1.3%	-0.3%	0.2%	-0.1%	-7.9%	-71,196
Canada	-9.9%	-30.2%	-33.1%	-16.9%	-11.6%	-6.4%	-6.5%	-3.0%	-2.9%	-0.9%	-0.2%	-0.3%	-9.9%	-2,847,402

TABLE 7. Impact on GDP Relative to Counterfactual by Province in All Scenarios (All Sectors)

	Opti	mistic	Dr. 1	Doom	End of	Tourism	Kill	l Fun	2nd	Wave
	%	\$M	%	\$M	%	\$M	%	\$M	%	\$M
AB	-6.8%	-25,978	-8.9%	-34,109	-8.9%	-34,121	-7.3%	-28,113	-11.0%	-42,176
BC	-8.9%	-25,428	-12.0%	-34,198	-12.1%	-34,428	-9.7%	-27,622	-14.3%	-39 <i>,</i> 887
MB	-6.2%	-4,352	-8.8%	-6,218	-9.1%	-6,421	-6.8%	-4,767	-10.4%	-7,276
NB	-6.7%	-2,283	-9.9%	-3,379	-9.5%	-3,225	-7.1%	-2,439	-12.2%	-4,110
NL	-10.5%	-3,741	-12.9%	-4,588	-11.8%	-4,220	-11.0%	-3,917	-19.5%	-6,836
NS	-8.5%	-3,457	-12.0%	-4,860	-10.3%	-4,169	-8.9%	-3,618	-15.8%	-6,094
ON	-8.8%	-70,367	-11.8%	-94,151	-10.3%	-82,025	-9.4%	-74,935	-15.0%	-116,529
PE	-9.2%	-604	-12.1%	-794	-11.2%	-734	-9.5%	-624	-19.2%	-1,187
QC	-9.4%	-38,878	-12.4%	-51,313	-11.1%	-46,119	-10.0%	-41,624	-16.3%	-66,811
SK	-8.1%	-7,477	-10.3%	-9,484	-10.1%	-9,303	-8.6%	-7,862	-15.1%	-13,577
Canada	-8.4%	-182,564	-11.3%	-243,094	-10.4%	-224,766	-9.0%	-195,521	-14.4%	-304,483

	Opt	timistic	Dr.	Doom	End o	f Tourism	Ki	ll Fun	2nd	l Wave
	%	1,000s								
AB	-8.9%	-324,706	-10.5%	-384,286	-12.2%	-444,106	-9.9%	-362,651	-14.4%	-520,547
BC	-10.2%	-387,717	-12.3%	-466,097	-14.2%	-533,983	-11.4%	-432,395	-16.3%	-606,128
MB	-7.4%	-74,499	-9.0%	-91,484	-11.4%	-115,023	-8.5%	-85,910	-12.5%	-124,919
NB	-7.4%	-41,493	-9.7%	-54,914	-11.0%	-62,063	-8.2%	-46,330	-14.1%	-77,951
NL	-9.9%	-33,342	-12.3%	-41,398	-13.1%	-44,232	-11.3%	-38,018	-18.2%	-60,131
NS	-9.8%	-69,952	-12.1%	-86,421	-12.7%	-90,670	-10.6%	-75,958	-18.3%	-123,626
ON	-10.4%	-1,180,489	-12.4%	-1,407,926	-12.5%	-1,419,452	-11.2%	-1,276,602	-17.8%	-1,975,438
PE	-10.0%	-12,693	-11.9%	-15,216	-12.5%	-15,868	-10.3%	-13,166	-21.2%	-25,380
QC	-10.2%	-651,315	-12.7%	-805,761	-12.9%	-819,534	-11.3%	-719,262	-18.2%	-1,140,324
SK	-7.9%	-71,196	-9.8%	-88,746	-10.9%	-98,302	-8.9%	-80,242	-14.5%	-127,301
Canada	-9.9%	-2,847,402	-12.0%	-3,442,248	-12.7%	-3,643,233	-10.9%	-3,130,534	-16.9%	-4,781,746

TABLE 8. Impact on Hours Relative to Counterfactual by Province in All Scenarios (All Sectors)

6. Appendix 3: Recovery Plans by Province

BC: https://www2.gov.bc.ca/gov/content/safety/emergency-preparedness-response-recovery/COV 19-provincial-support/bc-restart-plan

AB: https://www.alberta.ca/alberta-relaunch-strategy.aspx

SK: https://www.saskatchewan.ca/government/health-care-administration-and-provider-

resources/treatment-procedures-and-guidelines/emerging-public-health-issues/2019-novel-

coronavirus/re-open-saskatchewan-plan

MB: https://www.gov.mb.ca/COVID19/restoring/approach.html

ON: https://www.ontario.ca/page/framework-reopening-our-province

QC: https://www.quebec.ca/en/health/health-issues/a-z/2019-coronavirus/gradual-resumption-activities-COVID19-related

NB: https://www2.gnb.ca/content/gnb/en/corporate/promo/COVID-19/recovery.html

NS: https://novascotia.ca/coronavirus/restriction-updates/

PE: https://www.princeedwardisland.ca/en/topic/renew-pei-together

NL: https://www.gov.nl.ca/COVID-19/alert-system/