Sectoral digital intensity and GDP growth after a large employment shock: A simple extrapolation exercise

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Abstract. We introduce a state-dependent algorithm with minimal data requirements for predicting output dynamics as a function of employment across industries and locations. The method generalizes insights of Okun (1963) by leveraging measures of industry heterogeneity. We use the algorithm to examine gross domestic product (GDP) dynamics following the COVID-19 pandemic of 2020, delivering informative projections of aggregate and sectoral output. Because the pandemic curtailed the ability to perform certain tasks at work, our application examines whether greater reliance on digital technologies can mediate employment and productivity losses. We use industry-level indices of digital task intensity and ability to work from home, together with publicly available data on employment and GDP for Canada, to document that: (i) employment responses after the shock’s onset are milder in digitally intensive sectors and (ii) conditional on the size of employment changes, GDP responses are less extreme in digitally intensive sectors. Our projections indicate a return to pre-crisis aggregate output within eight quarters of the initial shock with significant heterogeneity in recovery patterns across sectors.

Résumé. Intensité numérique sectorielle et croissance du PIB après un important choc sur le plan de l’emploi : un simple exercice d’extrapolation. Nous utilisons un algorithme dépendant de l’état avec des exigences minimales en matière de données pour prédire les dynamiques de production comme fonction de l’emploi dans plusieurs industries et lieux. La méthode généralise les observations de Okun (1963) en mettant à profit les mesures d’hétérogénéité de l’industrie. Nous utilisons l’algorithme pour examiner les dynamiques du produit intérieur brut (PIB) après la pandémie de COVID-19 de 2020, produisant ainsi des projections informatives sur la production globale et sectorielle. Puisque la pandémie a réduit la capacité d’exécuter certaines tâches au travail, notre application examine si le fait de miser davantage sur les technologies numériques peut atténuer les pertes d’emplois et de productivité. Nous avons recours à des indices à l’échelon de l’industrie sur l’intensité des tâches numériques et la capacité de travailler à la maison, de concert avec les données disponibles au public sur l’emploi et le PIB au Canada, en vue de documenter...
1. Introduction

While the pandemic episode of 2020 and the resulting confinement restrictions have led to substantial declines in employment (Bartik et al. 2020b, Coibion et al. 2020, Koebel and Pohler 2020, Lemieux et al. 2020, Jones et al. 2020), their impact has been heterogeneous across sectors (Cajner et al. 2020, Chopra et al. 2020, Blit 2020). Employment declines in certain industries may have significant consequences for aggregate productivity (Makridis and Hartley 2020), especially when a rise in unemployment in those sectors leads to declines in consumer demand (Guerrieri et al. 2020) and permanently scars consumer confidence (Kozlowski et al. 2020).

Managing a crisis in real time is challenging. Since macroeconomic estimates of sectoral, or even aggregate, productivity are not available when decisions are made, policy-makers often pursue policies based on roughly informed guesswork. The primary contribution of this paper is to develop an approach with minimal data demands for estimating the anticipated effects of a large employment shock on GDP growth across industries and locations.

Unlike a full analysis that requires time and the collection of detailed data on both aggregate and sectoral output after the initial shock, our approach builds on simple estimates of the elasticity between GDP and employment that can be obtained using readily available public data; crucially, the procedure exploits heterogeneity across sectors that differ in their occupational concentration of digital tasks (Gallipoli and Makridis 2018).1 To recover estimates of sectoral elasticities, we rely on variation unique to the 2008/2009 financial crisis as the closest and most recent example of a sharp drop in employment; we then use the sectoral elasticities to project output trajectories for the 2020 recessionary episode under various assumptions about the speed of the recovery. We show that such a nimble and undemanding approach can provide much needed, and surprisingly accurate, projections for disaggregated GDP dynamics during periods of extreme turbulence.

To motivate the empirical approach, we begin by quantifying the heterogeneous effects of restricted mobility regimes in Canada on employment declines across sectors. We create a sectoral “resilience” index to measure social interaction shocks, combining occupational digital task intensity (Gallipoli and Makridis

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1 We use digital intensity and information technology (IT) intensity interchangeably.
2018) with home-shorability intensity (Baylis et al. 2020). We provide the first evidence that sectors with a higher share of digitally intensive occupations and home-shorable jobs experienced substantially milder employment declines: a percentage point (pp) rise in job resilience is associated with 0.65 pp higher employment growth between February and April 2020, suggesting that higher resilience sectors support aggregate economic activity during periods of extreme turbulence.

In the second part of the paper, we examine employment and real GDP growth across sectors and illustrate how one can recover an elasticity that is suitable for extrapolating sectoral output. Given strong correlation between employment growth and measures of digital intensity, home-shorability and resilience at the onset of the pandemic, we let elasticities vary across two broad sectors corresponding to high and low resilience scores. This approach generalizes the insights of Okun (1963) to multiple sectors by allowing for heterogeneity in GDP sensitivity to employment changes. Estimates of elasticities are obtained using variation that is unique to the 2008/2009 financial crisis since that historical event presents the closest analogue to the magnitude of employment declines observed over the course of the pandemic. Such estimates are instrumental in constructing a state-dependent rule to infer likely patterns of disaggregated output.

The third part of the paper examines sector-specific recovery patterns. In our baseline, we posit that the duration of sectoral recoveries is consistent with historical patterns from the large employment losses of the 2008/2009 recession: the path of sectoral employment recoveries back to pre-crisis levels depend on both the size of initial job losses and on the (proportional) rebounds of employment head counts after the 2008/2009 recession.

These assumptions are motivated by the easy availability of data on (i) short-term employment losses after the onset of the shock (for illustration, we use only data for February to April 2020) and (ii) historical records from the severe recession of the late 2000s. Simplicity and ease of use are key aspects of the approach. Moreover, our procedure can be used to project a path for aggregate GDP under alternative hypotheses about employment recoveries. In robustness checks, we experiment with departures from baseline scenarios and extrapolate alternative state-dependent outcomes for GDP. Then, using more recent data releases, we assess how informative these projections are about realized outcomes and gauge their relative performance.

Having estimated aggregate dynamics, we shift our focus to the evolution of GDP in different industries and locations. Since sectoral vulnerabilities to productivity losses due to population confinement depend on the characteristics of the occupations within each industry (their digital intensity and home-shorability), we posit that sectoral elasticities are inversely proportional to industry-specific resilience measures. Through a functional form assumption,

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2 Recent studies on the productivity and sectoral adoption of work-from-home arrangements during the COVID-19 pandemic support these assumptions (Baylis et al. 2020, Morikawa 2020, Etheridge et al. 2020).
we relate the prevalence of high-resilience tasks within an industry to that sector’s capacity to sustain its productivity and output under restrictions on population interaction. In this sense, we are able to separately extrapolate GDP growth rates for each two-digit industrial sector and project heterogeneity in GDP growth across provinces. We benchmark our results by comparing data on disaggregated GDP values from February 2020 to February 2021 with the estimates generated by our model. In an additional robustness check, we also compare our results with similar calculations where we use an alternative index of sectoral sensitivity to confinement disruptions based on contact intensity (Dingel and Neiman 2020a).

A key advantage of this approach is its simplicity: by relying on the interaction of cross-sectional covariation between occupational tasks and measures of digital intensity and home-shorability, we obtain informative and reasonably sharp real-time estimates of aggregate GDP.3 A second advantage is that GDP forecasts transparently reflect the underlying conjectures about employment dynamics, facilitating comparisons across alternative hypothetical scenarios about the path of employment.

Some caveats are in order. First, the procedure relies on assumptions about the path of employment after the shock onset—a simplification that ignores equilibrium feedbacks working through prices. Nonetheless, since public health constraints limit the ability of workers to perform some tasks regardless of prices, positing specific employment paths for recoveries is a reasonable approximation during the pandemic. We provide a set of potential paths for the employment and GDP recoveries, considering different state-dependent scenarios over short and medium horizons. Second, the method relies on historical estimates of sectoral elasticities of GDP with respect to employment. While these elasticities can be verified only as more information becomes available, the functional form assumption itself can be refined to improve performance as new data accrue. Lack of initial accuracy is the price one pays to make timely projections about sectoral GDP and productivity responses with minimal data requirements. However, this approach does deliver valuable estimates that help policy-makers make real-time decisions.

Recovering GDP–employment elasticities from the large recession of 2008/2009 is important because it captures possible non-linear responses of GDP following unusually large shifts in worker head counts. To accommodate uncertainty about hiring intensity, we examine different employment recovery scenarios. Our main projections indicate that Canada’s would experience an annualized decline in real GDP between 5.9% and 1.6% between February

3 Using an even simpler approach that proportionally allocates reductions in GDP based on the share of digitally intensive workers, Makridis and Hartley (2020) found that the aggregate costs of a two month national quarantine came to roughly 10%, matching the 8% figure estimated by the IMF (https://tinyurl.com/y8hnvs2j).
2020 and February 2021. Preliminary data by Statistics Canada suggest that actual GDP in February 2021 was 2.5% below its February 2020 level. This is close to our more benign forecast thanks to a much faster employment recovery than after the 2008 recession.\(^4\) Our estimates become even more precise by conditioning on the more recent releases of actual employment changes for the months after May 2020, suggesting that our simple approach has merit.

Our projections demonstrate significant cross-industry heterogeneity that closely line up with realized output changes over the twelve months following the initial shock onset. The correlation between projected and actual sectoral growth rates is around 85\% and the model does a good job of predicting large drops in sectors like accommodation and food services, while implying much smaller changes in more resilient and digitally intensive sectors like wholesale/retail trade or professional, scientific and technical services. The latter sectors experienced small year-on-year output drops and may ultimately expand through a potential new era of structural change.

2. Data and measurement

Our primary data on sectoral economic activity comes from publicly available Statistics Canada records on real gross domestic product (GDP) in chained 2012 prices by industry up until March 2020 and on employment by industry and province up until May 2020.

To measure the digital intensity of a sector, we draw on the task-based index introduced by Gallipoli and Makridis (2018). The United States Department of Labor O*NET database contains information on a wide array of activities, skills, job requirements and more, all at the occupational level. Respondents for each occupation answer questions on an ordinal scale that denotes the importance and frequency that tasks in the occupation are completed.

We take the product of the frequency and importance indices (when both are available) to generate an overall intensity for relevant sub-indices relating to digital skills.\(^5\) Furthermore, because we are interested in classifying occupations according to their digital intensity over time, we take the 2004 to 2016 average index. Because we do not have an analogue of the O*NET for Canada, we crosswalk occupations from their US-based standard occupational classification

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4 For comparison, estimates by the IMF and OECD for Canada’s annualized real GDP over the same period ranged between 6.2\% and 8.4\% in the base case.

5 These sub-indices from the Department of Labor’s O*NET include: knowledge about computers and electronics, activities interacting with computers, programming, systems evaluation skills, quality control analysis, operations analysis, activities with updating and using relevant knowledge, technology design, activities analyzing data and information, activities processing information, knowledge with engineering and technology, activities managing material resources.
(SOC) code into the corresponding Canadian code, which operates at a roughly three-digit SOC level. Our index is also robust to using clustering methods, such as Ward’s or K-means, to create an index as a function of these inputs; we defer to the simpler approach for transparency. We have also examined the persistence of digital skill intensity within the same occupation over time, finding a coefficient of 1.069 when we regress scores from 2015–2016 on scores from 2004–2005 ($R^2 = 0.79$).

Gallipoli and Makridis (2018) find that increases in the share of digital workers are associated with decreases in the employment share of manufacturing, but with increases in productivity in both manufacturing and services. Workers in digitally intensive sectors also earn over 0.60 logged points more than their counterparts. This premium declines to 0.43 logged points only after controlling for demographic characteristics, including age, race, gender, family size and education. We further benchmark our index by comparing differences in annual earnings and hours worked between our measure and a more restrictive approach by Hecker (2005).

In addition, we employ a novel Canada-wide database about occupation-level risk to create a unique score for two-digit industries in a given province using the proportion of workers working from home in each four-digit occupation before the onset of the pandemic. For each province, we take an average of this score (weighted by the number of workers in each two-digit industry) and create a measure of home-shorable (HS). A similar method is used to create a HS index for all industries at a national level. Finally, for the purposes of our projections, we combine the digital intensity and HS measures by taking their product within each industry and province. By so doing, we create a merged measure that we call resilience. High resilience signifies a high score for the combination of digital intensity and HS.

**Descriptive statistics**

We begin with several descriptive statistics for our measures. For each province (and for the whole of Canada), figure 1 plots the share of workers classified as digitally intensive as per Gallipoli and Makridis (2018), the share of workers with home-shorable jobs (as per Baylis et al.’s 2020 “risk tool”) and the share of workers with high resilience. We find a correlation of 0.71 between the digital intensity and HS measures at the provincial level. Interestingly, there is little cross-sectional variation in the digital intensity measures across the major provinces with the average share of high digital intensity jobs in a province around 53%, whereas we see more inter-provincial variation in HS, with the average province-specific HS measure around 7.1%. This suggests

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6 The novel database on occupational characteristics was developed at the Vancouver School of Economics at the University of British Columbia (Baylis et al. 2020). We refer to home-shorable measures as HS when convenient. The correlation between home-shorable and Dingel and Neiman (2020a) is 0.24.
that the task-based measure of digital skills is more inclusive, whereas home-shorability narrowly reflects whether a job can be performed at home.

Next, we examine the distribution of these measures across industries. Figure 2 documents variation across two-digit industries in the share of digital workers, ranging from the low of 25% in accommodation and food services to the high of 85% in professional and technical services. There is similar variation when using the HS measure, ranging from accommodation and food services (again) with the lowest at 0.6% to professional and technical services at 11%. The agricultural sector is an outlier with a value of 36.8%; this exception exists because many people who work in the agricultural sector both live and work on their farms. The correlation between these two measures across industries (excluding agriculture) is 0.62.

3. Motivation, context and methodology

Why might digital intensity matter for explaining industry-level and aggregate productivity? Because of technological change, more products and services are provided digitally. Although organizations have adapted by
upgrading their physical capital, including the adoption of data-driven decision-making and enterprise systems, technological change has also led to an overall increase in the digital intensity of labour force activities (Gallipoli and Makridis 2018). In this sense, a shock to social interactions through mobility restrictions will more adversely affect organizations that rely more upon physical tasks than those that rely heavily on digital activities.

Emerging literature is already showing, for example, that firms with greater digital intensity have performed better after February 2020. For example, Bai et al. (2021) show that firms with a higher concentration of jobs that allowed for working-from-home had significantly better outcomes than their counterparts, including in sectors deemed “non-essential.” Similarly, Papanikolaou and Schmidt (2020) find that sectors with a higher fraction of employees who could not work remotely experienced greater declines in employment, expected revenue growth and stock market performance as well as greater probabilities of default. They also find that female and younger workers were more affected by these disruptions. Put together, exposure to the pandemic based on digital intensity is closely related with firm performance.

There are different ways of measuring exposure to the social isolation shock over the pandemic and its effects. Chopra et al. (2020) emphasize the endogenous self-isolation behaviours of concerned workers and characterize the optimal lockdown policy in the presence of labour supply responses that

FIGURE 2 Index for digitally intensive and home-shorable employees, by industry
NOTES: The figure plots an index for digital intensity and home-shorability of jobs based on occupation and industries measures of tasks in the United States (for digital intensity) and Canada (for home-shorability, HA). Appendix section A1 describes the process to compute these heterogeneity scores. The third bar plots the industry-specific resilience, i.e., the product of the digitally intensive and HS measure for each industry.
SOURCES: Statistics Canada (2020), Minnesota Population Center (2019), Gallipoli and Makridis (2018) and Baylis et al.’s (2020) occupation risk tool
account for workers’ self-insurance against infection risk. Their quantitative exercise, calibrated to British Columbia, suggests that policy effects might depend on the willingness of workers in different occupations to take on infection risk. Dingel and Neiman (2020a) use O*NET to code occupations as jobs that cannot be performed at home if certain conditions are not met. When measuring exposure to the pandemic, Dingel and Neiman (2020a) find that 37% of jobs can be performed entirely at home and account for 46% of US wages (for a discussion or related issues, see Bloom et al. 2015).

Baylis et al. (2020) take a related approach, drawing on input from public health experts in Canada to determine the set of characteristics—from both O*NET on jobs and the 2016 Census of Population on living arrangements—that were most relevant for viral transmission. Using factor analysis to create a risk index, Baylis et al. (2020) create an interactive tool that allows them to map the economic importance of occupations coupled with the risk of transmission at the four-digit occupation by three-digit sectoral level.

Our paper builds on these contributions in three ways. First, we expand the notion of sectoral resilience to include aspects of digital intensity that facilitate certain occupational tasks. Second, we suggest a way to employ measures of sectoral heterogeneity within a simple state-dependent algorithm that delivers informative projections of the effect of the COVID-19 pandemic on real GDP. Finally, we provide a relatively easy-to-implement procedure to characterize heterogeneity in GDP responses to the pandemic shock across locations and industries. Our approach exploits the close link between

7 Specifically, O*NET provides information on work context and general work activities. The occupation cannot be performed at home if: “Average respondent says they use email less than once per month (Q4); Average respondent says they deal with violent people at least once a week (Q14); Majority of respondents say they work outdoors every day (Q17 and Q18); Average respondent says they are exposed to diseases or infection at least once a week (Q29); Average respondent says they are exposed to minor burns, cuts, bites, or stings at least once a week (Q33); Average respondent says they spent majority of time walking or running (Q37); Average respondent says they spent majority of time wearing common or specialized protective or safety equipment (Q43 and Q44).” Moreover, it cannot be performed at home if: “Performing general physical activities is very important (Q16A); Handling and moving objects is very important (Q17A); Controlling machines and processes [not computers nor vehicles] is very important (Q18A); Operating vehicles, mechanized devices, or equipment is very important (Q20A); Performing for or working directly with the public is very important (Q32A); Repairing and maintaining mechanical equipment is very important (Q22A); Repairing and maintaining electronic equipment is very important (Q23A); Inspecting equipment, structures, or materials is very important (Q4A).”

8 Consistent with Baylis et al. (2020), Mongey et al. (2021) use the Dingel and Neiman (2020a) index and find that more economically vulnerable workers (e.g., less educated and lower income) were more adversely affected by social distancing policies.
employment and output, recognizing that the relationship may differ sharply for sectors with higher levels of digital intensity. In this sense, our methodological approach is general, allowing policy-makers and researchers to apply an index to generate real-time predictions about aggregate and sectoral GDP growth.

Finally, our paper provides additional perspective about the recovery from the pandemic across different geographic locations. Since provinces were heterogeneously affected as a result of not only viral diffusion (Benatia et al. 2020) but also digital intensity of the labour force, policy-makers have a keen interest in methods that deliver estimates of productivity and output in different locations. This interest is reinforced by the longer lag with which Statistics Canada releases province-specific data on output and employment.

3.1. Tracing out GDP recoveries

Modelling output after a period of extreme turbulence is challenging. For the pandemic episode under examination, the challenges are more severe because the turbulence is due to unusual circumstances, such as restrictions on social and economic activities, for which there is little or no precedent in recent history. This difficulty is compounded by our interest in the dynamics of GDP across sectors and locations and the fact that data for employment and output across industries and locations is released with a lag often many months after the initial aggregate estimates become available. These difficulties motivate our effort to develop a simple state-dependent extrapolation approach that can be used with easy-to-access publicly available data.

Given the focus on post-crisis output dynamics, we examine the relationship between output and employment as mediated by a third, intangible factor that changes the sensitivity of different sectors to employment (headcount) losses.

The notion that employment variation can be used to gauge the evolution of output has a long history in economics (e.g., Okun 1963, Ball et al. 2013). We posit an output function that reflects how the number of workers maps into post-crisis output changes given employment losses and industry-specific resilience. We let \( y \) denote output in the post-onset period \( t \) and sector \( i \):

\[
y_{it} = e_{it} \times f(e_{it}, z_i),
\]

where \( e_{it} \) is sectoral employment (headcounts) and \( f(e_{it}, z_i) \) is a function capturing differential responses of \( y \) to \( e \) across industries due to heterogeneity in resilience \( z_i \).\(^9\) For the empirical implementation below, we assume

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\(^9\) Given our focus on short-term and medium-term recoveries after initial onset, we abstract from physical capital. When we take the model to the data, we consider specifications that include controls for the industry-specific capital stock and find that estimates are not significantly different.
\[ f(e_{it}, z_i) = \xi z_i + e_{it}^{\xi z_i}, \]
so that the heterogeneity in \( z_i \) is reflected in the post-recovery growth trend and sensitivity to employment levels.

The idea that some sectors might do better than others in terms of employment, GDP, or both, is plausible, given that sectors are heterogeneously exposed to the pandemic restrictions. To the extent that HS and IT intensity can cushion against the adverse effects of social distancing measures, one should observe heterogeneous responses across those dimensions, and we explore this possibility in a simple and transparent way.

We proceed in two steps. First, we assume that the sectoral resilience \( z_i \) reflects the adoption and penetration of digital and IT technology in production practices. We follow Gallipoli and Makridis (2018) and partition industries into two groups (digitally and non-digitally intensive) on the basis of whether they fall above or below the median share of IT intensity, as defined by the tasks performed by workers in their occupations.

Panel A of figure 3 provides evidence in support of the hypothesis that higher prevalence of digitally intensive jobs mitigates the impact of confinement shocks on an industry: a strong positive relationship exists between digital intensity and employment growth between February and April 2020, right after confinement measures became widely adopted across Canadian provinces. Industries with a 10% higher share of IT intensive workers have a 4.1% higher growth rate of employment.

Panels B and C of figure 3 replicate these patterns using the measures of HS and of overall resilience; the latter is defined as the product of digital intensity and HS. By combining variation about digital intensity and home-shorability, we obtain a more encompassing proxy for gauging the responsiveness of industries to the pandemic shock.

**Sectoral elasticities**

Are there differences across sectors in the dynamic responses of output to employment after the initial crisis onset? This is a harder question because it requires information about the evolution of head counts, which is not readily available. For this reason, we estimate a linear approximation for the growth rates of the sectoral output function in equation (1); this provides a concise description of industry-specific GDP responses to employment changes. We use different sample intervals between January 2001 and April 2020 at a monthly frequency to establish whether this relationship is significantly different during a crisis (e.g., 2008–2009) through regressions of the form

\[ \Delta y_{it} = \gamma \Delta e_{it} + \zeta z_i + \xi (\Delta e_{it} \times z_i) + \epsilon_{it}, \]

(2)

where \( \Delta y_{it} \) denotes the year-to-year growth rate of (real) GDP in industry \( i \) and month–year \( t \), \( \Delta e_{it} \) denotes the year-to-year growth rate of employment for the same industry–period pair and \( z \) denotes a binary indicator for whether the industry is in a relatively more resilient group, that is, above or below median according to a measure of choice. We estimate the latter
Panel A: Employment declines and digital intensity

Panel B: Employment declines and home-shorability

Panel C: Employment declines and resilience

FIGURE 3  Employment declines after onset of the pandemic across sectors
NOTES: The figure plots employment growth between February and April 2020 within an industry and digital-intensity score, home-shorability and resilience in panels A, B and C, respectively. Since the agriculture industry is an outlier in the home-shorability and resilience index for reasons unrelated to the primary research question of interest, we have excluded its values from the estimation of the figures in panels B and C.
SOURCES: Statistics Canada (2020), Minnesota Population Center (2019), Gallipoli and Makridis (2018), Baylis et al.’s (2020) occupation risk tool
relationship for two groups (high and low resilience), rather than for each industry, to improve precision; better data quality, and additional sources of variation, would allow for more flexible estimation.

Given the evidence in figure 7, we expect that $\xi < 0$, meaning that the more digitally intensive sectors should experience less of a decline over the pandemic. We estimate equation (2) under several specifications: with and without the $z$ interaction, over the extended sample and for the subsample corresponding to the recovery following the 2008–2009 recessionary episode. The latter, restricted subsample is especially informative because it exploits variation unique to GDP-employment changes after a deep and wide economic downturn, shedding light on the way different industries respond, particularly during periods of significant economic turbulence when the elasticity is large.

Table 1 documents the findings from this exercise. Starting with column 1, we see that a 1pp rise in employment is associated with a 0.72pp rise in GDP over the extended sample period. Given the potential for reverse causality, we instrument for employment growth using two to three month lags following Arellano and Bond (1991); this delivers statistically indistinguishable (and slightly higher) coefficient estimates in column 2. When we restrict the sample to the turbulent 2008–2009 period, we obtain similarly large elasticities with a notable increase in the $R^2$. This lends some support to the use of the elasticities estimated for those years to assess GDP dynamics after the COVID-19 shock. Results are similar when we allow for differences in resilience across sectors.

### Table 1

| Dep. var. = |   |   |   |   |   |
|-------------|---|---|---|---|---|
| Real GDP growth |   |   |   |   |   |
| (1) | (2) | (3) | (4) | (5) | (6) |
| Employment growth | 0.73*** | 0.76*** | 0.78*** | 0.91*** | 0.91*** | 0.84*** |
|                  | [0.05] | [0.05] | [0.05] | [0.05] | [0.06] | [0.06] |
| High resilience  | 0.01*** | 0.01*** | 0.03*** | 0.01*** | 0.03*** |
| $\times$ Employment growth | -0.51*** | -0.42*** | -0.43*** |
| R-squared | 0.36 | 0.36 | 0.54 | 0.41 | 0.41 | 0.62 |
| Sample size | 3,450 | 3,405 | 360 | 3,450 | 3,405 | 360 |
| Sample | All | All | 2008–2009 | All | All | 2008–2009 |
| Instrument | No | Yes | No | No | Yes | No |

**Notes:** The table reports the coefficients associated with regressions of industry $\times$ month real GDP growth (year-to-year, in chained 2012 prices) on employment growth, interacted with an indicator for whether the sector has high resilience (high IT intensive and home-shorable jobs). The latter exposure is measured using IPUMS Canada 2011 data in conjunction with the digital intensity measure and the home-shorability measure. We instrument the potentially endogenous employment growth with two and three month lagged values of the year-to-year growth rate. Including sectoral measures of capital in this regression does not alter our estimates.

**Sources:** Gallipoli and Makridis (2018), Baylis et al.’s (2020) occupational risk tool and Statistics Canada.

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**TABLE 1**

| Elasticity of GDP growth to employment growth |
|---------------------------------------------|
| Dep. var. = Real GDP growth | (1) | (2) | (3) | (4) | (5) | (6) |
| Employment growth | 0.73*** | 0.76*** | 0.78*** | 0.91*** | 0.91*** | 0.84*** |
| High resilience  | 0.01*** | 0.01*** | 0.03*** | 0.01*** | 0.03*** |
| $\times$ Employment growth | -0.51*** | -0.42*** | -0.43*** |
| R-squared | 0.36 | 0.36 | 0.54 | 0.41 | 0.41 | 0.62 |
| Sample size | 3,450 | 3,405 | 360 | 3,450 | 3,405 | 360 |
| Sample | All | All | 2008–2009 | All | All | 2008–2009 |
| Instrument | No | Yes | No | No | Yes | No |
Turning to column 6, which restricts our sample to the so-called Great Recession period, we see that a 1pp rise in employment is associated with a 0.84pp rise in GDP in low resilience sectors, but with only a 0.41pp rise in GDP in the high resilience sectors. This evidence suggests that job resilience acts as a mediating force that mitigates the impact of employment changes on output during times of economic turbulence. One potential concern with these results is that differences in the capital stock could be correlated with the share of digital workers and with sectoral elasticities. To examine this possibility, we experiment with including capital stocks for different industries as an additional control; estimates are robust to this additional heterogeneity.10

4. Projecting recovery paths

4.1. Baseline: “Great Recession” recovery path

In the baseline case, we impose a linear employment recovery starting in May 2020 and leading back to the level of employment last observed in February 2020. We posit that the duration of the employment rebound is analogous to what was observed after the recession of the late 2000s.11

One way to indirectly validate the assumed duration of employment recoveries is to compare the year-on-year employment growth rates between May 2019 and May 2020 (as measured by Statistics Canada) with those implied by a linear recovery path mimicking that of the previous recession. As shown in table 2, predicted and actual employment drops are close, providing some corroboration for the assumed pace and horizon of the employment recovery. At least initially, it appears that the baseline conjecture about the evolution of head counts is reasonable.

Next, we condition on the assumed employment changes after April 2020 to project GDP using the baseline elasticity estimates in column 6 of table 1. After normalizing output in February 2020 to 1, we extrapolate GDP levels for both low resilience and high resilience industries as well as for the pooled sample of all industries. The left panel of figure 4 reports these projections alongside realize GDP changes up until the most recent data release of February 2021; the figure highlights that aggregate output bottomed out in April 2020, at roughly 82% of its pre-crisis level. The recovery starting in the summer of 2020 is projected to bring aggregate GDP back to its pre-crisis level

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10 Given these findings, and the objective to develop a procedure that can be implemented with minimal data requirements, we do not use these additional specifications. Moreover, because we do not make GDP projections for agriculture, we do not include it in the analysis of table 1. Results including agriculture are almost identical. All results are available upon request.

11 In that episode, it took an average of 21 months for employment in low resilience industries to revert to pre-crisis levels, whereas it took about 30 months in high resilience industries.
before the end of 2021. Peak-to-through output losses are shallower, at around 8%, in high resilience industries, as opposed to a drop of roughly 15% for low resilience industries.

Comparing projected and realized output paths between February 2020 and February 2021, the model understates the initial drop and the pace of the subsequent recovery. This is especially conspicuous in the low-resilience sector, consistent with the observation that the employment recovery in heavily hit sectors was faster than expected (Jones et al. 2020, Brochu et al. 2020). The right panel of figure 4 corroborates this observation because it shows GDP projections based on realized employment paths up until February 2021 versus actual GDP changes. The gap between projected and actual values is much smaller in this case, indicating that the discrepancy, especially in the low-resilience sector, is due to the conservative assumption of slower employment growth. The figure suggests that the bounce back in employment after the pandemic episode was stronger than after the 2008/2009 credit market crisis. Yet, despite its limitations, our simple projection algorithm does a fairly good job of estimating both aggregate and sectoral GDP growth with minimal

|                  | Statistics Canada | Estimated     |
|------------------|-------------------|---------------|
| Low resilience   | −16.6%            | −17.9%        |
| High resilience  | −8.4%             | −8.4%         |
| All industries   | −13.5%            | −14.3%        |

**NOTE:** The table shows the annual (year-on-year) employment growth rates reported between May 2019 and May 2020 by Statistics Canada and the same annual employment growth rates as estimated by our baseline employment recovery scenario.  
**SOURCES:** Gallipoli and Makridis (2018) and Statistics Canada (2020)
data requirements and with significant uncertainty about the employment recovery. Revising projections as employment data become available notably improves prediction performance, making the algorithm a useful tool to update projections in real time during a crisis.

**Year-on-year output growth rates**

Appendix figure A1 presents an alternative way to summarize the baseline estimates for the post-crisis evolution of GDP with the yearly GDP growth rates for different quarters. The figure shows the rate of growth under several scenarios alongside actual growth until February 2021. All projections indicate a return to year-on-year growth in the second quarter of 2021, which seems likely given the most recent GDP figures released by Statistics Canada.

**4.2. Faster employment rebound: An optimist’s view**

March and April 2020 saw large losses in national employment levels, although high resilience industries experienced much smaller proportional employment losses than low resilience industries. As many jurisdictions began easing mandatory confinement of workers, and businesses started to re-open with social distancing measures in place, the Canadian economy witnessed a strong month-on-month increase in employment in May 2020, with about 300,000 jobs added to the employment tally. Jones et al. (2020) provide a detailed snapshot of the Canadian labour market as of June 2020, with a special focus on the faster than expected recovery in vacancy postings and in “recalled” workers (those workers who were laid off after the COVID-19 shock and then recalled by their original employers). Given this rebound, one might expect that the elimination of strict mobility curbs would go a long way towards bringing back many of the furloughed workers to active employment. That is, one might take the hopeful view that employment would recover faster than it did after the recession of 2008/2009.

Guided by this observation, we consider an alternative and optimistic scenario that assumes an accelerated recovery. We posit comparatively large employment gains in June and July 2020, similar to those observed in May. We also assume that, after a summer spike in hiring, employment keeps growing at a more gentle pace until we get back to pre-crisis levels of employment, around March 2021 in the non-IT industries and November 2021 in IT-intensive industries. As before, differences across industries in the pace of employment reflect the observation that recovery was faster in the non-IT sectors after the recessionary episode of 2008. The recovery duration for employment under this scenario is roughly 60% of that assumed in the baseline case.

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12 Huang et al. (2020) use high-frequency data from the United States to show that the removal of stay-at-home orders and nonessential business closures was associated with a roughly 20% to 26% increase in employment and hours worked in retail and hospitality sectors.
Figure 5 shows the evolution of normalized GDP, suggesting the economy might get back to pre-crisis output levels by the end of 2021 or the beginning of 2022. Remarkably, this optimistic projections provide a rather precise match to actual GDP growth between May and February 2021, confirming that the employment recovery has been faster than what was observed after the 2008 contraction. Figure A1 reports the annual GDP growth rates for different quarters of the recovery under this alternative scenario in which positive year-on-year growth would return much earlier, within the first few months of 2021.

4.3. Comparing recovery scenarios

The alternative scenarios outlined above correspond to different assumptions about employment paths, following the initial onset of the shock. To facilitate comparisons, figure 6 plots in the same graph the post-onset evolution of (normalized) aggregate GDP for both baseline and benign employment outlooks. The solid line in the figure reports actual GDP changes until the most recent monthly release date (February 2021), confirming two basic observations: (i) while smoother than the real GDP changes, projections from our algorithm do a fairly good job of approximating monthly GDP levels and (ii) the optimistic

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**Figure 5** Optimistic GDP forecast, by resilience

**NOTES:** The graph reports GDP levels for low resilience sectors, high resilience sectors and all industries calculated using the values of GDP predicted using our model in equation (2) for a more optimistic employment recovery. GDP is normalized to 1 in February 2020. All GDP level estimates are reported in table A1.

**SOURCES:** Gallipoli and Makridis (2018), Baylis et al.’s (2020) occupational risk tool and Statistics Canada (2020)
projection captures monthly GDP levels almost exactly after May 2020, suggesting a faster employment recovery than the baseline 2008/2009 assumption.

These projections entail two sources of uncertainty on employment changes and GDP–employment elasticity. Most of the discrepancy between realized and predicted GDP can be attributed to uncertainty about future employment dynamics; to further substantiate this claim, in figure 6, we superimpose the baseline GDP projection obtained using realized employment counts until the most recent data release, which was February 2021. This exercise illustrates that month-to-month GDP increments can be approximated remarkably well when preliminary headcount measures are available.

Most of the uncertainty concentrates around the period of early 2021 because the outcomes depend so heavily on the path of infections and employment. The difference in predicted GDP levels between different scenarios is large immediately after onset. The gap shrinks as we approach the end of 2021 as uncertainty is resolved.

5. Sectoral and provincial heterogeneity in GDP paths

Disaggregated monthly data on industry-specific GDP is currently available up to February 2021. Province-level figures for GDP are not available on a
monthly basis. Yet it is often necessary to venture in the risky business of estimating potential patterns of GDP. Our stylized approach can deliver such estimates across industries and locations even in the immediate absence of detailed data on employment and productivity after the onset of a large shock. We draw information about the share of digitally intensive and home-shorable jobs in each industry and use these measures to proportionally scale real output within each period x industry unit. For example, an industry with an 80% share of digitally intensive workers, who remain productive at home, could sustain a smaller output loss during periods of reduced social interactions than an industry where only 20% of tasks are digitally intensive.

**Functional form restrictions**

To capture the sectoral sensitivity of GDP while preserving aggregation, we calibrate period-specific (month–year) GDP response elasticities $\varepsilon_m$ relative to baseline values in February 2020. In practice, this rescales sectoral output to be a fraction of its pre-crisis level under the constraint that, in any given month, aggregate output is taken as given. The calibration exercise can be repeated for every month during the recovery period: each $\varepsilon_m$ parameter captures GDP changes for period $m$ and can be used to project sectoral output to a specific month during the employment recovery. Sectoral GDP projections depend on industry-specific digital resilience according to

$$Y_m = \sum_{i=1}^{n} y_{FEB \times i} \left(1 - \frac{\varepsilon_m}{r_i}\right),$$

where $Y_m$ denotes aggregate GDP in a given month $m$, $y_{FEB \times i}$ is baseline GDP of industry $i$ in February 2020 and $r_i$ is industry $i$’s resilience.

To bring this specification to data, we employ the estimates of monthly aggregate GDP obtained in the previous section in conjunction with industry-specific real GDP data for February 2020 (as released by Statistics Canada) and resilience measures based on Gallipoli and Makridis (2018) and the Baylis et al.’s (2020) occupational risk tool. This information is sufficient to compute a sequence of elasticities $\varepsilon_m$—one for each month.

In turn, the elasticities can be used to calculate the projected GDP for each industry $i$ in a given month $m$. This is done using equation (4), which spells out each element on the right-hand side summation of equation (3); that is, we denote GDP in industry $i$ and period $m$ as

$$y_{m \times i} = y_{FEB \times i} \left(1 - \frac{\varepsilon_m}{r_i}\right).$$

We follow this procedure for both baseline and optimistic recovery scenarios and measure GDP growth for each industry between February 2020 and February 2021, which is the most recent period for which we have data on GDP releases by industry. Figure 7 documents projected GDP growth projections vis-à-vis real GDP changes by industry.
Not surprisingly, industries that rely on consistent social interactions (e.g., accommodation/food services) did suffer much larger output drops, with some of them exceeding 10% over the one-year period we consider. By the same token, professional and scientific industries and education services experienced much milder changes. Finance, insurance and real estate industries even registered growth over the period. This heterogeneity in industry growth rates is consistent with our working assumption that digital intensity and home-shorability mitigate and diffuse the severity of both employment and productivity losses. The correlation between projected and real growth rates over the February-to-February period is high (0.847).

Figure 7 shows that our algorithm generates projections that closely track, both qualitatively and quantitatively, the GDP changes published by Statistics Canada. Given the low data and implementation demands entailed in these predictions, the procedure provides a useful tool for policy-makers interested in gauging the asymmetric effects of a large employment shock.

**GDP growth rates across provinces**

One can follow a similar approach to project GDP growth for different provinces. That is, one can use the relationship in equation (4) under the
assumption that index $i$ identifies a location, rather than an industry. The main difference lies in the fact that we do not currently have monthly real GDP data disaggregated by province; therefore, we must recover the February baseline GDP values by calculating the GDP contribution of each province in February 2020. To do this, we use the most recent GDP share data released by Statistics Canada for the year 2019. We then estimate unique month-specific values of the elasticity of GDP for each province, based on province-specific resilience measures (the same measures we reported in table 1). We also impose an adding-up constraint so that provincial GDP values sum up to the aggregate GDP in each month. Figure 8 documents the implied year-on-year GDP growth under both the baseline and optimistic scenarios. While digital intensity does not markedly vary across provinces, the resilience measure does. Year-on-year GDP drops between February 2020 and February 2021 are projected highest for Newfoundland and Labrador, between 8.9% and 2.8%, and smallest for Saskatchewan, between 3.7% and 1.1%. The bounds correspond to the baseline and optimistic scenarios, respectively. BC is also projected to experience a

![Estimated GDP growth from Feb 2020 to Dec 2020, by province](image)

**FIGURE 8** Expected GDP growth in 2020 using occupational resilience measures, by province

**NOTES:** Based on authors' calculations of resilience using Gallipoli and Makridis’s (2018) IT intensity index and Baylis et al.'s (2020) home-shorability, we estimate GDP values with equation (2). We then use the process explained in section 5 to estimate GDP by province for 2020 and report GDP growth from February 2020 to February 2021. We were not able to calculate exact growth rates for each territory because Statistics Canada does not provide specific data required to make these estimations. Table A4 provides estimated GDP growth values for each jurisdiction.

**SOURCES:** Statistics Canada (2020), Minnesota Population Center (2019)
milder drop, between 4.8% and 1.5%. It is important to recognize that the losses in each province will depend on their ability to restrain the spread of infection and on the effectiveness of mitigation efforts. Location-specific differences in infection prevalence, even more than job and industry characteristics, will ultimately determine where each province ends up. Differences in provincial growth rates are likely to be more dispersed than our projections since they will reflect heterogeneity in the severity of local infections. Recent work (Benatia et al. 2020) suggests stark differences in both the levels of population infection rates and trends across provinces. Nonetheless, in the absence of monthly data on local GDP dynamics, our estimates provide a valuable gauge of heterogeneity in provincial growth rates.

5.1. Contact intensity and industry heterogeneity

So far, we have focused on heterogeneity in resilience that reflects sectoral IT task intensity and home-shorability of jobs. Other sources of job heterogeneity may affect outcomes during a pandemic. For example, measures of industry-specific contact intensity (see Dingel and Neiman 2020a) indirectly capture the adaptability of jobs to work-from-home arrangements by their need for human contact when performing basic tasks. Unsurprisingly, these measures are positively correlated with digital intensity and home-shorability: the correlation between the contact intensity index of Dingel and Neiman (2020a) and the home-shorability measures of the Baylis et al. (2020) is 0.24; the correlation between contact intensity and our augmented resilience measure is slightly higher, at 0.37.

Given its distinct focus and popularity, Dingel and Neiman’s (2020a) contact intensity is a suitable candidate for robustness exercises that illustrate how one can adapt our state dependent extrapolation algorithm to explore alternative sources of sectoral heterogeneity. We classify industries into high and low contact intensity groups (above and below median) and re-estimate the GDP–employment elasticities under this alternative characterization of sectoral heterogeneity. The estimates, presented in column (6) of table 3, can then be used to project GDP growth by industry and location.

In figure 9, we plot realized and projected GDP growth between February 2020 and February 2021 based on Dingel and Neiman’s (2020a) contact intensity. The average magnitude of estimated GDP drops across industries is similar to our benchmark results; perhaps more interestingly, relative differences in industry-specific growth rates are also similar to those reported in the baseline analysis, suggesting that our state-dependent projections are fairly robust to the use of alternative measures to capture sectoral heterogeneity in jobs’ resilience during the pandemic. More generally, given the simplicity of the state-dependent approach used to project growth rates, one could combine several alternative measures of industry heterogeneity to generate a richer set of estimates. The scalability of our simple extrapolation approach is one of its main advantages.
### TABLE 3
Elasticity of GDP growth to employment growth

| Dep. var. = | Real GDP growth | (1) | (2) | (3) | (4) | (5) | (6) |
|------------|-----------------|-----|-----|-----|-----|-----|-----|
| Employment growth | 0.72*** | 0.76*** | 0.78*** | 0.78*** | 0.81*** | 0.79*** |
| [0.05] | [0.05] | [0.05] | [0.05] | [0.06] | [0.05] |
| High contact intensity | 0.01*** | 0.01*** | 0.03*** | 0.00 | 0.00 | 0.00 |
| × Employment growth | −0.29*** | −0.27*** | −0.28*** | 0.07 | 0.07 | 0.08 |
| R-squared | 0.36 | 0.36 | 0.54 | 0.38 | 0.38 | 0.65 |
| Sample size | 3,450 | 3,405 | 360 | 3,450 | 3,405 | 360 |
| Sample | All | All | 2008–2009 | All | All | 2008–2009 |
| Instrument | No | Yes | No | No | Yes | No |

**NOTES:** The table reports the coefficients associated with regressions of industry × month real GDP growth (year-to-year, in chained 2012 prices) on employment growth, interacted with an indicator for whether the sector has high exposure to information technology-intensive (IT-intensive) jobs. The latter exposure is measured using IPUMS Canada 2011 data in conjunction with the Gallipoli and Makridis (2018) IT-intensity measure. We instrument the potentially endogenous employment growth with two and three month lagged values of the year-to-year growth rate.

**SOURCES:** Gallipoli and Makridis (2018), Dingel and Neiman (2020b) and Statistics Canada (2020)
6. Conclusion

When a wide-reaching shock hits the economy, there is invariably an urgency to come up with estimates about its likely impact. The COVID-19 pandemic has generated much speculation about its implications for economic output, both in aggregate and across sectors, given the unusual nature and size of the shock involved. The main objective of our work is to suggest a simple state-dependent procedure that can provide meaningful projections of GDP dynamics with minimal implementation and data requirements. We show that such a procedure can leverage readily available data, such as employment and output, from statistical institutes, like Statistics Canada.

Our procedure builds on the classic work of Okun (1963), linking employment and output, and generalizes it to multiple sectors by exploiting direct measures of heterogeneity (across occupations, industries and locations). Given its simplicity, the procedure can be easily scaled to include alternative measures of sectoral and geographic heterogeneity.

To illustrate how sectoral heterogeneity can be leveraged, we present evidence that sectors with greater digital intensities, and job home-shorability, are less exposed to confinement shocks such as those observed during a pandemic (Blit 2020, Jones et al. 2020). We then estimate the degree of...
heterogeneity in sectoral elasticities of real GDP to employment growth and employ these estimates to extrapolate bounds for GDP growth over the months following the onset of the shock: a percentage point rise in the resilience of workers is associated with 0.54 percentage point higher employment growth between February and April 2020.

We consider alternative paths for GDP and employment. The baseline projection suggests that the economy would shrink by over 10% during the spring of 2020 and then gradually recover to resume year-on-year positive growth by the spring of 2021. However, the pre-crisis GDP level is unlikely to be reached before the first quarter of 2022. These aggregate patterns hide significant differences across sectors: in low resilience sectors year-on-year GDP drops are predicted to be much larger relative to high resilience industries. Under a more benign scenario, in which we let employment recover faster than in the previous recessionary episode, aggregate GDP would return to pre-crisis levels by the end of 2021. When we assess the performance of our projection algorithm using recently released data on monthly GDP growth between February 2020 and 2021, we find that it provides an informative and surprisingly accurate approximation of GDP dynamics, especially after the initial GDP drop. Sectoral projections align well quantitatively and qualitatively with preliminary readings of actual output changes.

Our forecasts do not explicitly model the effects of comprehensive government stimulus or interventions to help cushion the adverse effects of the crisis. For example, the passage of the Paycheck Protection Program in the United States has generated a body of empirical work that is likely to grow in the next few years. While much of the preliminary evidence suggests that the program had fairly insignificant effects on employment and wages (Granja et al. 2020, Autor et al. 2020, Chetty et al. 2020), potentially because the first round of funds were not allocated to the businesses that needed it most (Granja et al. 2020), the topic remains hotly debated (Bartik et al. 2020a, Hubbard and Strain 2020, Faulkender et al. 2020). We leave open the possibility that researchers amend our methodological approach with different policy scenarios. The key question, however, is how the intervention mediates the path of employment within and across sectors that vary in their exposure to the aggregate shock.

While time will tell how (in-)accurate these forecasts are, they provide a data-driven and transparent way to gauge the impact of the COVID-19 pandemic on aggregate and sectoral output. The analysis highlights the importance of differences in occupational task intensities, specifically related to the digital economy, in mediating employment and output declines. Projected GDP growth rates vary significantly across industries, with a handful of them shouldering most of the output losses. Future research might explore how governments and organizations in different sectors have adapted to the changes over the course of the recovery (Gunderson 2020) and how layoffs in certain sectors translate into lower future GDP.
Appendix: Procedures, tables and figures

A1. Procedures to compute heterogeneity scores

IT intensity scores for industries (figure 2)
There is a binary value for high and low IT intensity (1 or 0) given according to the z-itscores for three-digit SOC levels. We merge this with the cleaned IPUMS file and collapse the binary values by industry. This gives us a unique score for each industry. This score is plotted in figure 2.

IT intensity score for provinces (figure 1)
We use employment data of provinces by industry from 2019 and merge it with the unique industry score calculated above. We calculate the product of this industry IT score and number of people in the industry in that province (\(\text{ind}_\text{prov}_\text{highit}_\text{occ}\)). We then find the sum of \(\text{ind}_\text{prov}_\text{highit}_\text{occ}\) for each province and divide it by the number of working people in that province. This gives us a unique value for each province which is the province-specific IT intensity plotted in figure 1.

![Annual GDP growth (\%), by quarter](image)

**FIGURE A1** Quarterly GDP growth rates

**NOTES:** GDP growth for each quarter is defined as the average of the annual growth rate estimated for each month of the quarter. The annualized GDP growth rates from February 2020 to January 2022 are reported in table A2. For the January to March 2021 quarter, we use only real GDP changes from January and February, since the March figures have not yet been released.

**SOURCES:** Gallipoli and Makridis (2018), Baylis et al.’s (2020) occupational risk tool and Statistics Canada
Home-shorability score for industries for Canada (figure 2)
We have the number of people \( n_{\text{workers}} \) in a four-digit occupation and the proportion of people working from home \( wfh \) in that occupation throughout Canada. We collapse the number of people working in four-digit occupations by two-digit industries (called \( n_{\text{total}} \)) to find the number of people in an industry. We find the share of people from an occupation working in an industry \( \text{share}_\text{occ}_\text{ind} \) by dividing \( n_{\text{workers}} \) by \( n_{\text{total}} \). We then find the product of the \( wfh \) and \( \text{share}_\text{occ}_\text{ind} \) and collapse it by industry. This gives us a unique score for each industry for Canada, reported in figure 2.

Home-shorability score for provinces (figure 1)
Using the same procedure defined above, we can calculate a unique score for each industry in a given province. We then calculate the share of workers from an industry in a particular province \( \text{share}_\text{ind}_\text{prov} \) by dividing the number of workers in an industry with the number of workers in that province. Then we find the product of the unique industry score and share of workers in that industry in the province and call it \( \text{score}_\text{share}_\text{prov} \). When we collapse this, we get a unique number for the given province. This can be repeated for each province to find the score which is then reported in figure 1.

Resilience (figures 1 and 2)
It is the product of the IT intensity score and home-shorability score for each province and industry.

### TABLE A1
GDP levels (February 2020 normalized to one)

| Date    | Baseline | | | Baseline | | | | Benign outlook | | | |
|---------|----------|-----------------|-----------------|----------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
|         | Aggregate| Low resilience | High resilience | Aggregate| Low resilience | High resilience | Aggregate| Low resilience | High resilience | Aggregate| Low resilience | High resilience |
| Feb. 2020 | 1.000     | 1.000          | 1.000           | 1.000     | 1.000          | 1.000           | 1.000     | 1.000          | 1.000           | 1.000     | 1.000          | 1.000           |
| Mar. 2020 | 0.929     | 0.911          | 0.949           | 0.929     | 0.911          | 0.949           | 0.929     | 0.911          | 0.949           | 0.929     | 0.911          | 0.949           |
| Apr. 2020 | 0.884     | 0.825          | 0.950           | 0.884     | 0.825          | 0.950           | 0.884     | 0.825          | 0.950           | 0.884     | 0.825          | 0.950           |
| May. 2020 | 0.897     | 0.846          | 0.953           | 0.897     | 0.846          | 0.953           | 0.897     | 0.846          | 0.953           | 0.897     | 0.846          | 0.953           |
| Jun. 2020 | 0.903     | 0.855          | 0.956           | 0.903     | 0.855          | 0.956           | 0.903     | 0.855          | 0.956           | 0.903     | 0.855          | 0.956           |
| Jul. 2020 | 0.907     | 0.858          | 0.962           | 0.907     | 0.858          | 0.962           | 0.907     | 0.858          | 0.962           | 0.907     | 0.858          | 0.962           |
| Aug. 2020 | 0.909     | 0.862          | 0.962           | 0.909     | 0.862          | 0.962           | 0.909     | 0.862          | 0.962           | 0.909     | 0.862          | 0.962           |
| Sep. 2020 | 0.914     | 0.867          | 0.966           | 0.914     | 0.867          | 0.966           | 0.914     | 0.867          | 0.966           | 0.914     | 0.867          | 0.966           |
| Oct. 2020 | 0.918     | 0.873          | 0.968           | 0.918     | 0.873          | 0.968           | 0.918     | 0.873          | 0.968           | 0.918     | 0.873          | 0.968           |
| Nov. 2020 | 0.925     | 0.881          | 0.974           | 0.925     | 0.881          | 0.974           | 0.925     | 0.881          | 0.974           | 0.925     | 0.881          | 0.974           |
| Dec. 2020 | 0.931     | 0.889          | 0.977           | 0.931     | 0.889          | 0.977           | 0.931     | 0.889          | 0.977           | 0.931     | 0.889          | 0.977           |
| Jan. 2021 | 0.935     | 0.896          | 0.979           | 0.935     | 0.896          | 0.979           | 0.935     | 0.896          | 0.979           | 0.935     | 0.896          | 0.979           |
| Feb. 2021 | 0.941     | 0.904          | 0.983           | 0.941     | 0.904          | 0.983           | 0.941     | 0.904          | 0.983           | 0.941     | 0.904          | 0.983           |
| Apr. 2021 | 0.941     | 0.911          | 0.975           | 0.941     | 0.911          | 0.975           | 0.941     | 0.911          | 0.975           | 0.941     | 0.911          | 0.975           |
| Jul. 2021 | 0.957     | 0.930          | 0.987           | 0.957     | 0.930          | 0.987           | 0.957     | 0.930          | 0.987           | 0.957     | 0.930          | 0.987           |
| Oct. 2021 | 0.967     | 0.944          | 0.993           | 0.967     | 0.944          | 0.993           | 0.967     | 0.944          | 0.993           | 0.967     | 0.944          | 0.993           |
| Jan. 2022 | 0.984     | 0.967          | 1.003           | 0.984     | 0.967          | 1.003           | 0.984     | 0.967          | 1.003           | 0.984     | 0.967          | 1.003           |

(continued)
### TABLE A1 (continued)

|          | Baseline (realized employment) | Real data |
|----------|-------------------------------|-----------|
|          | Aggregate | Low resilience | High resilience | Aggregate | Low resilience | High resilience |
| Feb. 2020 | 1.000     | 1.000          | 1.000          | 1.000     | 1.000          | 1.000          |
| Mar. 2020 | 0.929     | 0.911          | 0.949          | 0.929     | 0.911          | 0.949          |
| Apr. 2020 | 0.884     | 0.825          | 0.950          | 0.821     | 0.747          | 0.904          |
| May. 2020 | 0.897     | 0.846          | 0.953          | 0.858     | 0.803          | 0.919          |
| Jun. 2020 | 0.932     | 0.904          | 0.963          | 0.908     | 0.880          | 0.940          |
| Jul. 2020 | 0.946     | 0.921          | 0.975          | 0.931     | 0.905          | 0.960          |
| Aug. 2020 | 0.951     | 0.927          | 0.978          | 0.939     | 0.911          | 0.971          |
| Sep. 2020 | 0.962     | 0.934          | 0.994          | 0.947     | 0.921          | 0.977          |
| Oct. 2020 | 0.965     | 0.935          | 0.998          | 0.955     | 0.928          | 0.985          |
| Nov. 2020 | 0.970     | 0.940          | 1.003          | 0.962     | 0.939          | 0.988          |
| Dec. 2020 | 0.969     | 0.938          | 1.004          | 0.964     | 0.939          | 0.991          |
| Jan. 2021 | 0.954     | 0.924          | 0.988          | 0.972     | 0.951          | 0.995          |
| Feb. 2021 | 0.965     | 0.939          | 0.994          | 0.975     | 0.952          | 1.001          |
| Apr. 2021 | 0.966     | 0.947          | 0.987          | ..        | ..             | ..             |
| Jul. 2021 | 0.980     | 0.963          | 0.998          | ..        | ..             | ..             |
| Oct. 2021 | 0.990     | 0.977          | 1.003          | ..        | ..             | ..             |
| Jan. 2022 | 1.007     | 1.001          | 1.014          | ..        | ..             | ..             |

**NOTES:** This table gives us the levels of GDP for a month when compared with the level of GDP of February 2020 (which is considered to be 1). We have three different scenarios: baseline, optimistic and second wave. Each scenario has the GDP level reported for aggregate GDP, GDP of low resilience industries and GDP of high resilience industries. We use equation (2) to estimate annual GDP growth rates, given an assumed path of employment growth for each scenario. These GDP growth rates are then used to recover the evolution of GDP levels, as presented in this table. Throughout all three scenarios, we observe an unexpected drop in employment levels only in March and April 2020. This gives us a sudden drop in the employment and GDP levels for March 2021 as they depend upon the employment levels in March 2020. To overcome this challenge of our model, we calculate the employment growth rate of March 2021 with respect to the average employment level of March and April 2020 i.e., (employment in March 2021 – average of employment in March 2020 and April 2020)/(average of employment in March 2020 and April 2020). This employment growth rate is then used as per the model to compute GDP growth rate and levels.

**SOURCES:** Gallipoli and Makridis (2018), Baylis et al.’s (2020) occupational risk tool and Statistics Canada
### TABLE A2
Annualized GDP growth rates (percentages)

| Date    | Baseline Aggregate | Baseline Low resilience | Baseline High resilience | Benign outlook Aggregate | Benign outlook Low resilience | Benign outlook High resilience |
|---------|--------------------|-------------------------|--------------------------|--------------------------|-------------------------------|-------------------------------|
| Feb. 2020 | 2.468              | 1.995                   | 3.003                    | 2.468                    | 1.995                         | 3.003                         |
| Mar. 2020 | -5.544             | -5.765                  | -0.110                   | -5.544                   | -5.765                        | -0.110                        |
| Apr. 2020 | -10.583            | -17.575                 | -2.550                   | -10.583                  | -17.575                       | -2.550                        |
| May. 2020 | -9.532             | -15.705                 | -2.444                   | -9.532                   | -15.705                       | -2.444                        |
| Jun. 2020 | -9.085             | -14.922                 | -2.390                   | -8.213                   | -13.365                       | -2.304                        |
| Jul. 2020 | -8.546             | -14.138                 | -2.199                   | -6.902                   | -11.213                       | -2.008                        |
| Aug. 2020 | -8.278             | -13.459                 | -2.426                   | -5.957                   | -9.359                        | -2.114                        |
| Sep. 2020 | -7.953             | -13.001                 | -2.644                   | -5.054                   | -7.934                        | -1.809                        |
| Oct. 2020 | -7.465             | -12.084                 | -2.289                   | -4.071                   | -6.209                        | -1.674                        |
| Nov. 2020 | -6.843             | -11.190                 | -1.993                   | -3.059                   | -4.695                        | -1.233                        |
| Dec. 2020 | -6.585             | -10.804                 | -1.865                   | -2.536                   | -3.925                        | -0.982                        |
| Jan. 2021 | -6.229             | -10.142                 | -1.853                   | -2.018                   | -3.045                        | -0.869                        |
| Feb. 2021 | -5.870             | -9.582                  | -1.719                   | -1.609                   | -2.466                        | -0.651                        |
| Apr. 2021 | 6.453              | 10.387                  | 2.631                    | 11.500                   | 19.283                        | 3.937                         |
| Jul. 2021 | 5.483              | 8.439                   | 2.539                    | 7.058                    | 10.328                        | 3.696                         |
| Oct. 2021 | 5.341              | 8.137                   | 2.522                    | 3.762                    | 4.283                         | 3.205                         |
| Jan. 2022 | 5.211              | 7.853                   | 2.505                    | 1.734                    | 0.835                         | 2.717                         |

### Baseline (realized employment)

| Date    | Aggregate | Low resilience | High resilience | Aggregate | Low resilience | High resilience |
|---------|-----------|----------------|-----------------|-----------|----------------|-----------------|
| Feb. 2020 | 2.468    | 1.995          | 3.003           | 2.440    | 2.022          | 2.912           |
| Mar. 2020 | -5.544   | -5.765         | -0.110          | -5.548   | -8.214         | -2.502          |
| Apr. 2020 | -10.583  | -17.575        | -2.550          | -16.969  | -25.400        | -7.284          |
| May. 2020 | -9.532   | -15.705        | -2.444          | -13.491  | -19.958        | -6.066          |
| Jun. 2020 | -6.139   | -10.061        | -1.639          | -8.553   | -12.390        | -4.151          |
| Jul. 2020 | -4.601   | -7.819         | -0.948          | -6.130   | -9.336         | -2.491          |
| Aug. 2020 | -4.082   | -6.966         | -0.825          | -5.310   | -8.580         | -1.615          |
| Sep. 2020 | -3.069   | -6.261         | 0.529           | -4.585   | -7.541         | -1.253          |
| Oct. 2020 | -2.738   | -5.822         | 0.718           | -3.822   | -6.586         | -0.724          |
| Nov. 2020 | -2.346   | -5.254         | 0.899           | -3.111   | -5.285         | -0.686          |
| Dec. 2020 | -2.728   | -5.913         | 0.836           | -3.282   | -5.713         | -0.562          |
| Jan. 2021 | -4.327   | -7.386         | -0.906          | -2.545   | -4.546         | -0.310          |
| Feb. 2021 | -3.477   | -6.077         | -0.570          | -2.528   | -4.838         | 0.057           |
| Apr. 2021 | 9.237    | 14.727         | 3.903           | .        | .              | .               |
| Jul. 2021 | 3.530    | 4.606          | 2.393           | .        | .              | .               |
| Oct. 2021 | 2.555    | 4.485          | 0.533           | .        | .              | .               |
| Jan. 2022 | 5.564    | 8.325          | 2.677           | .        | .              | .               |

**NOTES:** This table shows the annualized growth rate as calculated by our model in equation (2) in percentage. Annualized growth rate refers to the rate of growth between a month from year to year. This has been reported for all three scenarios for aggregate GDP, low resilience industries and high resilience industries.

**SOURCES:** Gallipoli and Makridis (2018), Baylis et al.’s (2020) occupational risk tool and Statistics Canada Canada
### TABLE A3
Expected GDP growth (%) in 2020 following Gallipoli and Makridis (2018), by industry

| Industries                                      | GDP growth (baseline) | GDP growth (benign outlook) | Real GDP growth |
|------------------------------------------------|-----------------------|----------------------------|-----------------|
| All industries                                 | −5.419                | −1.595                     | −2.211          |
| Utilities                                      | −4.811                | −1.416                     | −2.514          |
| Construction                                   | −8.448                | −2.487                     | 0.267           |
| Manufacturing                                  | −9.108                | −2.681                     | −3.274          |
| Wholesale and retail trade                     | −5.654                | −1.664                     | 2.537           |
| Business, building and other support services   | −7.907                | −2.328                     | −10.070         |
| Mining, quarrying, oil and gas                 | −5.086                | −1.497                     | −5.601          |
| Transportation and warehousing                 | −11.846               | −3.487                     | −19.321         |
| Finance, insurance, real estate, rental and leasing | −1.653                | −0.487                     | 4.078           |
| Professional, scientific and technical services | −1.521                | −0.448                     | 0.777           |
| Educational services                           | −3.895                | −1.146                     | −0.573          |
| Health care and social assistance              | −5.281                | −1.554                     | −0.115          |
| Information, culture and recreation            | −2.150                | −0.633                     | −10.735         |
| Accommodation and food services                | −27.642               | −8.137                     | −39.503         |
| Other services (except public administration)  | −3.181                | −0.936                     | −12.337         |
| Public administration                          | −4.026                | −1.185                     | −1.001          |

**NOTES:** Based on authors’ calculations of resilience using Gallipoli and Makridis’s (2018) IT intensity index and Baylis et al.’s (2020) occupational risk tool’s home-shorability, we then use the estimates of GDP values calculated in section 4 in the baseline and delayed scenario to follow the process explained in section 5 to estimate GDP by Industry for 2020 and report GDP growth from February 2020 to February 2021 in this table.

**SOURCES:** Statistics Canada, Minnesota Population Center (2019)
### TABLE A4

Expected GDP growth (%) in 2020 following Gallipoli and Makridis (2018), by province

| Provinces                        | GDP growth (baseline) | GDP growth (benign outlook) |
|----------------------------------|-----------------------|-----------------------------|
| Canada                           | −6.352                | −2.670                      |
| Alberta                          | −6.031                | −2.535                      |
| British Columbia                 | −5.474                | −2.301                      |
| Manitoba                         | −6.913                | −2.905                      |
| New Brunswick                    | −8.235                | −3.461                      |
| Newfoundland and Labrador        | −10.287               | −4.324                      |
| Nova Scotia                      | −7.390                | −3.106                      |
| Ontario                          | −6.383                | −2.683                      |
| Prince Edward Island             | −8.174                | −3.436                      |
| Quebec                           | −6.909                | −2.904                      |
| Saskatchewan                     | −4.242                | −1.783                      |

**NOTES:** Based on authors’ calculations of resilience using Gallipoli and Makridis’s (2018) IT intensity index and Baylis et al.’s (2020) occupational risk tool’s home-shorability, we then use the estimates of GDP values calculated in section 4 in the baseline and delayed scenario to follow the process explained in section 5 to estimate GDP by province for 2020 and report GDP growth from February 2020 to February 2021 in this table. We were not able to calculate exact growth rates for each territory because Statistics Canada does not provide specific data required to make these estimations.

**SOURCES:** Statistics Canada, Minnesota Population Center (2019)

### A2. Tables and figures

### TABLE A5

Expected GDP growth (%) in 2020 following Dingel and Neiman (2020), by industry

| Industries                                      | GDP growth (baseline) | GDP growth (benign outlook) | Real GDP growth |
|-------------------------------------------------|-----------------------|----------------------------|-----------------|
| All industries                                  | −4.524                | −1.480                     | −2.211          |
| Utilities                                       | −4.676                | −1.530                     | −2.514          |
| Construction                                    | −8.748                | −2.862                     | 0.267           |
| Manufacturing                                   | −6.778                | −2.217                     | −3.274          |
| Wholesale and retail trade                      | −4.184                | −1.369                     | 2.537           |
| Business, building and other support services    | −4.921                | −1.610                     | −10.070         |
| Mining, quarrying, oil and gas                  | −5.112                | −1.672                     | −5.601          |
| Transportation and warehousing                  | −7.251                | −2.372                     | −19.321         |
| Finance, insurance, real estate, rental and leasing | −2.671              | −0.874                     | 4.078           |
| Professional, scientific and technical services | −2.435                | −0.796                     | 0.777           |
| Educational services                            | −2.311                | −0.756                     | −0.573          |
| Health care and social assistance               | −4.378                | −1.432                     | −0.115          |
| Information, culture and recreation             | −3.062                | −1.002                     | −10.735         |

(continued)
TABLE A5  
(Continued)

| Industries                               | GDP growth (baseline) | GDP growth (benign outlook) | Real GDP growth |
|------------------------------------------|-----------------------|-----------------------------|-----------------|
| Accommodation and food services          | −8.400                | −2.748                      | −39.503         |
| Other services (except public administration) | −4.468                | −1.462                      | −12.337         |
| Public administration                     | −3.270                | −1.070                      | −1.001          |

NOTES: Based on authors’ calculations using Dingel and Neiman’s (2020b) work from home index, we estimate GDP values for a baseline and delayed scenario with equation (2) and elasticities in column (7’) of table 3. We then use the process explained in section 5 to estimate GDP by Industry for 2020 and report GDP growth from February 2020 to February 2021 in this table.

SOURCES: Statistics Canada, Minnesota Population Center (2019)

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