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Benchmarks for assessing labour market health

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Overview

This staff analytical note serves as a complement to past work to assess labour market slack (see Ens et al. 2021). That earlier work proposed a more granular framework for assessing slack, given how diverse and segmented the labour market is.

Benchmarks used in that paper were set to pre-COVID-19 levels—specifically, their 2019 average. These benchmarks are still appropriate for the current period when the labour market is recovering from COVID-19. But as we get further away from 2019, and as the effects of the pandemic wane, the question becomes which benchmarks are most appropriate for assessing labour market health on an ongoing basis.

To help answer this question, in this note we do four things:

- We review possible approaches to benchmarking labour market progress, including historical levels and trend estimates.
- Given disadvantages inherent in each of the individual approaches, we propose the use of a range. Using a range can help answer questions that have a high degree of uncertainty, such as questions about the level of sustainable maximum employment. Indicators above the range would be consistent with a labour market operating above what would be expected based on its historical performance.[1]
- We show the importance of annual updates to benchmarks to account for population aging and structural changes in the labour market such as digitalization.
- We compare the newly constructed range against the 2019 average. We find that the 2019 average is at the higher end of the benchmarks we explore; as a result, comparing the status of the labour market against a broader set of benchmarks suggests even more strength in the Canadian labour market. Accounting for population aging since 2019 also suggests even more strength, notably for older workers as well as for the overall employment and participation rates.

On balance, the Canadian labour market appears to have more than fully recovered from the COVID-19 shock and, by any benchmark examined, has considerable strength.

[1] A broader range of data and information, including on inflation, would be needed to make a final determination about whether maximum sustainable employment had been reached.

Assessment of different benchmarking approaches

In this section, we discuss benchmarking approaches, including their advantages and drawbacks.

See **Box 1** for a discussion of the non-accelerating inflation rate of unemployment (NAIRU). Although it is often used to assess overall labour market health, we do not consider the NAIRU because it is not applicable to a wider set of measures.

Historical maximums and minimums. A useful starting point is to examine the historical maximums and minimums for each labour market indicator.[2] Knowing these levels allows us to compare current levels with the best level an indicator has achieved. This provides important context.

Despite its simplicity, benchmarking against historical maximums and minimums also presents some challenges. Many labour market data series are non-stationary (i.e., the statistical properties of these variables, such as the mean, are not constant over time), which means it may not be feasible for some variables to return to their historical bests. For example, the labour force participation rate is likely to be lower than its historical best going forward as the population continues to age. Thus, while they are useful in providing a signal of what the labour market has achieved, historical maximums and minimums require some consideration of the past and current context. Other measures can complement historical maximums and minimums by accounting for trend changes.

Trend estimates from filters. To address issues of non-stationarity, trend estimates can be used to account for ongoing structural changes in the labour market. To derive trend estimates, we use standard filtering techniques—either a two-sided filter such as the Hodrick-Prescott (HP) filter (Hodrick and Prescott 1997), or a one-sided filter such as the Hamilton filter (Hamilton 2018).

- The HP filter is a widely used tool to extract the trend component of any given time series. Applying the HP filter to data involves decomposing a data series into a trend component and a residual or cyclical component.[3] The HP filter is widely adopted in applied macroeconomic work. Nevertheless, certain precautions are required when interpreting the results from this filter. The HP filter is known to suffer from end-point issues. In particular, the last point in the data series can have an outsized impact on the estimation of trend

[2] For some indicators, such as the unemployment rate, the historical minimum is interpreted as its historical best, whereas for other indicators, such as the participation rate, the historical maximum would correspond to its historical best. Where appropriate, we define "best" and "worst" in terms of an indicator's relationship to the health of the labour market.

[3] For the benchmark presented in this note, we use a smoothing parameter of 900,000 (100,000) for monthly (quarterly) series.

versus cycle.[4] Given that the most recent data points in the labour market continue to cover the pandemic period, this makes the estimation of trend particularly challenging in the current context. The severe adverse impact of the pandemic also complicates the estimation of trend before the pandemic.[5] Further, a very large but one-time adverse shock can cause the HP filter to misattribute the data as reflecting a lower trend.

- Unlike the two-sided HP filter, the Hamilton filter is purely backward-looking. It is based on the notion that the cyclical component of a series can be defined as the difference between the actual value of the series $t + h$ periods ahead of what would be predicted based on historical information up to period t. In other words, any time series can be decomposed into a trend and a cyclical component by running the following linear regression model, where the dependent variable y_{t+h} is regressed against its value at date t, y_t, together with up to p lagged values from date t:

$$y_{t+h} = \beta_0 + \beta_1 y_t + \beta_2 y_{t-1} + \cdots + \beta_{p+1} y_{t-p} + v_{t+h},$$

  where p represents the number of lags in the series.[6] Because it is backward-looking in nature, the Hamilton filter is not subject to the same end-point problems as the HP filter. Nonetheless, the Hamilton filter has its own drawbacks. Since it does not incorporate the newest information, the trend from this filter is slow moving. Consequently, new information and deviations from the past are mostly attributed to cycle.

Beyond the HP and Hamilton filters, the Bank of Canada also computes its own trend estimates of the unemployment rate, the employment rate and average hours worked. It uses regression models that control for various inputs that affect the demand for labour.[7] Because these regression models combine both contemporaneous and past information, the trend estimates produced have the benefit of being less slow moving than those derived from the Hamilton filter. Unlike the HP filter, these trend estimates are also less subject to end-point issues because these regression models do not penalize variability in the trend component. These trend

[4] The HP filter minimizes the following problem: $\min_{g_{t_{t=0}}^{T}}\{\sum_{t=1}^{T}(y_t - g_t)^2 + \lambda \sum_{t=1}^{T}[(g_t - g_{t-1}) - (g_{t-1} - g_{t-2})]^2\}$, where the first term corresponds to the variance in the cyclical component, and the second term corresponds to the variation in the second difference in the trend component g_t. λ is the smoothing parameter that penalizes the variation in the trend component. At end points, this penalty on the trend component is missing, causing the trend derived under the HP filter to be more responsive to shocks at the end of the sample.

[5] Appendix A shows how this effect is particularly pertinent to variables such as the unemployment rate, with observed trend estimates diverging once data on the pandemic period have been included.

[6] Later in this note, we include the Hamilton filter in our range of benchmarks. Specifically, we take the fitted values $\hat{y}_{t+h}$ as the trend component, while the estimated residuals $\hat{v}_{t+h}$ become the cyclical component. We use the suggested values of $h = 8$ for quarterly data and $h = 24$ for monthly data, representing a two-year gap between the value being predicted and the latest information being used to accomplish this. We set p such that one year of lagged data is used.

[7] For trend employment rate and trend average hours worked, age- and sex-specific employment rate and average hours worked are regressed against their own lagged values as well as a set of cyclical labour demand variables and structural factors (e.g., age and cohort effects, employment insurance disincentives, real after-tax interest rate). Trends are then obtained as the aggregated dynamic fitted values arising from the regression. See Barnett (2007) for more details. The Trend Unemployment Rate is estimated as a weighted average of trend estimates from models with structural determinants and multivariate state-space models as described in Brouillette et al. (2019).

estimates are computed for only a limited number of aggregate series, however—specifically the employment rate, average hours worked and the unemployment rate. Applying the same regression model to other series, such as the labour utilization rate or the share of long-term unemployed, may not be straightforward because different factors may underlie the performance of more disaggregated indicators and different series.

Finally, we note the following critique for all trend estimates. Conducting a trend-cycle decomposition after a large shock is particularly challenging because it is difficult to disentangle cycle from trend if temporary shocks lead to permanent changes in the economy. In the current context, such decompositions may be subject to significant revisions as data evolve after the pandemic.

Benchmarking against when the labour input (LI) gap is closed. One alternative signpost considers what each labour market indicator's value was during the most recent period when the LI gap is estimated to have been closed.[8] This is a useful benchmark as it may reflect a period when the labour market was close to its capacity. A benefit of this measure is that a single period is identified, and we can compare the values of each labour market indicator in that period to its current value. This allows for a broad-based assessment of how far the current state of the economy may be from achieving the same closure in the LI gap.

While simple and clear, this measure also suffers from the same drawbacks as the historical maximums and minimums, in the sense that the underlying data series are non-stationary and may never reach the same levels as in the past. Further, LI , which itself is an aggregate measure, can mask distributional outcomes. The period when the LI gap is closed may be characterized by exceptionally high employment rates for one group but severely low employment rates for another. This could result in using too low benchmarks for subgroups.

Comparing subgroups with the broader population. An additional way to compare labour market outcomes across groups would be to do direct comparisons, for example, benchmarking youth employment rates against those of prime-age workers. While such comparisons are easy to analyze and communicate, different demographic groups may have structural differences that make it unlikely for their labour market outcomes to align. These structural differences could include different levels of education and skills training, systemic barriers in the labour market, and job preferences that differ by age. Consequently, having a greater understanding of the structural challenges faced by vulnerable groups in the labour

[8] Labour input (or total hours worked) is determined by the size of the working-age population, the employment-population ratio and the average hours worked per week. The Bank estimates trend labour input (TLI) as a combination of working-age population and labour market trends. Specifically, key inputs for the trends include historical data on age- and sex-specific employment rate and average hours worked, cyclical and structural variables, and group-specific population data and projections. The labour input gap is simply the difference between TLI and observed labour input. We find that the most recent period during which this gap closed is in 2019. Given that the selected period represents a static benchmark, we adjust the 2019 average value of selected benchmarks, such as the employment rate and labour force participation rates (both in aggregate and across groups), to account for demographic changes.

market could help policy-makers better assess slack and potentially identify ways to better integrate more workers into the labour force.

Box 1

Challenges of using the non-accelerating inflation rate of unemployment as a benchmark

The non-accelerating inflation rate of unemployment (NAIRU) is a commonly used benchmark to assess the labour market. In practice, however, the NAIRU is difficult to estimate accurately and can further mask areas of weakness in the labour market.

The NAIRU is the lowest unemployment rate that can be sustained in the economy without causing inflation to rise. The concept of the NAIRU suggests that there is a trade-off between inflation and unemployment. In the short run, changes in aggregate demand or monetary policy can cause unemployment and inflation rates to move in opposite directions. This trade-off between unemployment and inflation is best seen through the lens of the Phillips curve:

$$\Delta\pi_t=\beta(u_t^*-u_t)+x_t,$$

where $\Delta\pi_t$ is the change in the expected inflation rate, u_t is the unemployment rate, u_t^* represents the NAIRU, and x_t controls for supply shocks. The above equation highlights how unemployment rates below the NAIRU can give rise to inflationary pressures.

While the Phillips curve succinctly captures the trade-off between unemployment and inflation, the above equation also demonstrates the difficulty in estimating u_t^*. The above equation contains three unknowns (β,u_t^*,x_t) and only two observables ($\Delta\pi_t,u_t$), making it highly difficult to accurately estimate u_t^*. Even if we assume the absence of supply shocks (or that such shocks do not correlate with unemployment) and that the NAIRU has a constant value, i.e., $u_t^*=u^*$, it is unclear whether running a regression on the change of inflation against the unemployment rate should yield a coefficient β that is time invariant. In other words, β is not immutable to policy changes or structural changes in the economy, the latter of which may have been accelerated or precipitated by the onset of the recent pandemic. Moreover, the assumption that the NAIRU is a constant value has non-trivial implications It assumes that u^* is immutable to structural shifts in the labour market, when the unemployment rate by definition is affected by changes in both the employment rate and the participation rate, both of which have seen long-term changes over time. Because of these difficulties in computing the NAIRU, most measures of u_t^* are poorly estimated.

Finally, because the NAIRU itself captures only aggregate unemployment, it may not be able to reflect certain areas of slack in a diverse or segmented labour market, especially during periods of strong disagreement across various indicators. As Ens et al. (2021) note, the NAIRU could mask weakness or slack in other headline measures of the labour market (e.g., participation, vacancies), the quality of jobs being created or distributional outcomes (e.g., demographic groups, short-term versus long-term unemployment). For example, the unemployment rate could be low on average despite a slow recovery of participation and long-term unemployment or the presence of large disparities in employment gains across groups.

Constructing a range of benchmarks

In the previous section, we explained how various benchmarks can each provide valuable information on labour market strength. But we also highlighted how they each have drawbacks, resulting in a lot of uncertainty around the use of any single approach. To address this issue, we propose the use of a range of benchmarks:

- the HP filter
- the Hamilton filter
- the most recent period during which the labour input gap was closed

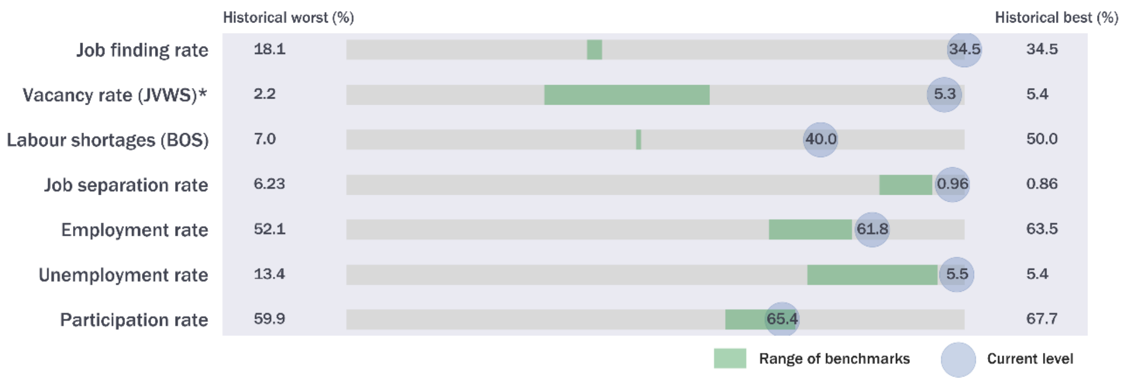
The Bank produces trend estimates for specific variables, such as the unemployment rate, the employment rate and average hours worked. We also include these in our range of estimates.

Chart 1, **Chart 2** and **Chart 3** demonstrate how the current state of the labour market compares with the range of trend estimates. The length of the horizontal axis represents the historical minimum and maximum (since 2003) and acts as the upper and lower bounds for each labour market variable. The historical maximum (i.e., best performance) of the indicator is not being proposed as a target; rather, it reflects the upper bound of the indicator's past historical values. The relevant benchmarks are captured in the shaded range.[9] Values that fall below the range point to labour market weakness. Values within the range are consistent with historical performances. And values above the range point to a labour market that is exceeding what would be expected based on past trends. In the case where many measures sit above the range

[9] A smaller range suggests more agreement among benchmarks; a wider range, less agreement.

of benchmarks, non-labour market information will also be needed to assess whether maximum sustainable employment has been reached (e.g., indicators of capacity pressures, inflation).

Chart 1: Measures of overall labour market conditions



Note: This chart presents the current value of labour market indicators when compared with their historical best and historical worst. Benchmarks are comprised of the Hamilton filter, the Hodrick-Prescott filter, the corresponding value of the indicator during a period when the labour input gap was closed and, for selected indicators, trend estimates produced by the Bank of Canada. Data for all series are from Statistics Canada's Labour Force Survey (LFS) unless otherwise noted. BOS is Business Outlook Survey; JVWS is Job Vacancy and Wage Survey.
*Vacancy rate data are from 2015 onward and may affect trend estimates.

Sources: Statistics Canada, Bank of Canada and Bank of Canada calculations

Last observations: LFS, February 2022; BOS, 2022Q1; JVWS, 2021Q4

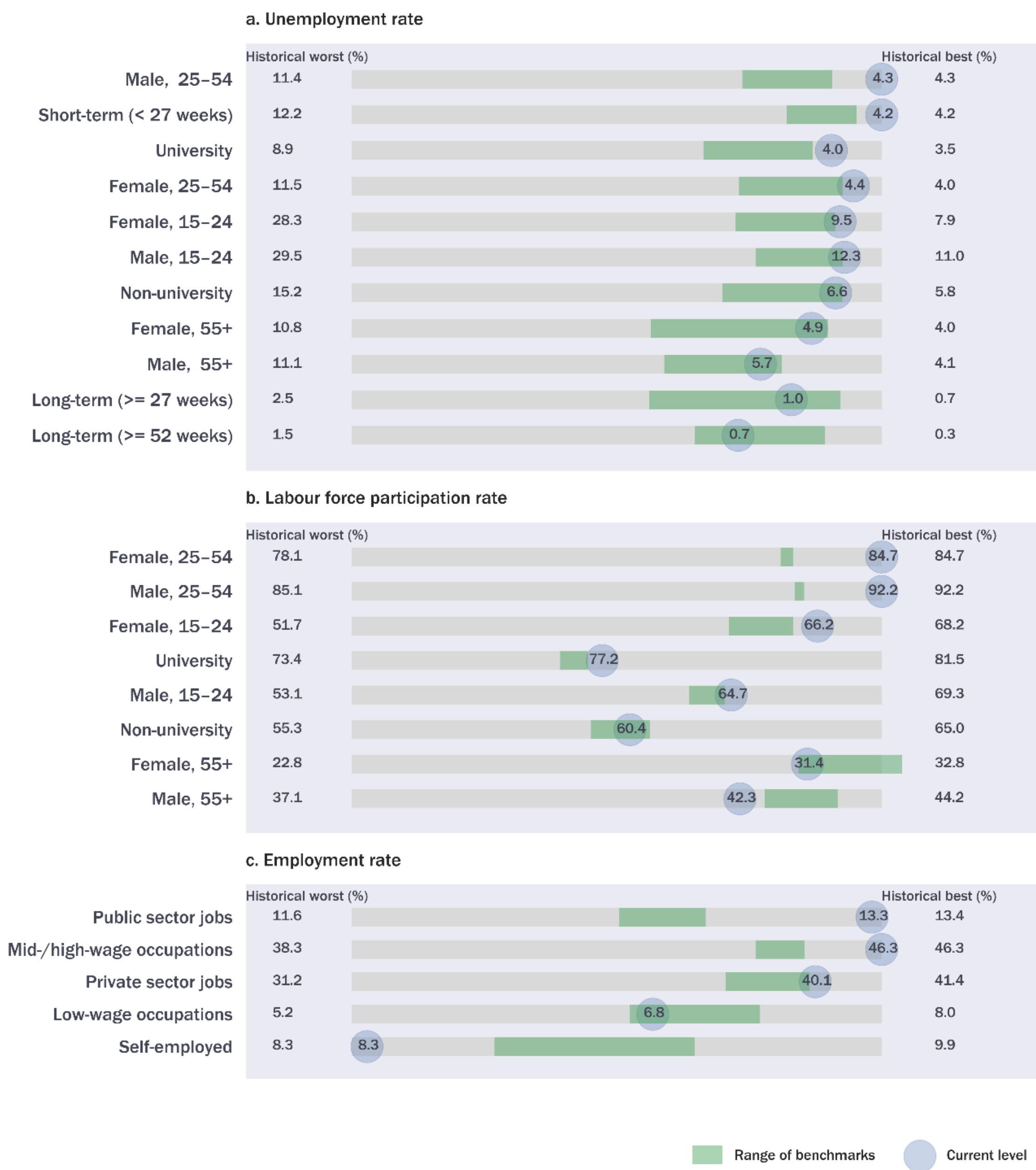
Chart 2: Measures of job characteristics

Note: This chart presents the current value of labour market indicators when compared with their historical best and historical worst. Benchmarks are comprised of the Hamilton filter, the Hodrick-Prescott filter, the corresponding value of the indicator during a period when the labour input gap was closed and, for selected indicators, trend estimates produced by the Bank of Canada. Data for all series are from Statistics Canada's Labour Force Survey (LFS) unless otherwise noted. SEPH is Survey of Employment, Payrolls and Hours.
*Average hours worked are expressed in hours and not percent.

Sources: Statistics Canada, Bank of Canada and Bank of Canada calculations

Last observations:
LFS, February 2022;
SEPH, January 2022;
national accounts, 2021Q4;
national accounts (wage measure), December 2021

Chart 3: Measures of labour market inclusiveness



Note: This chart presents the current value of labour market indicators when compared with their historical best and historical worst. Benchmarks are comprised of the Hamilton filter, the Hodrick-Prescott filter, the corresponding value of the indicator during a period when the labour input gap was closed and, for selected indicators, trend estimates produced by the Bank of Canada. Employment levels by wage are not seasonally adjusted.

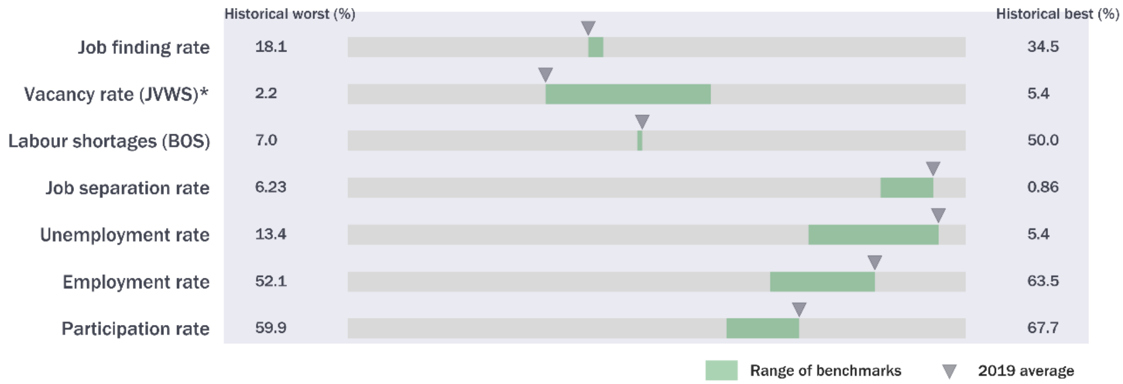
Sources: Statistics Canada and Bank of Canada calculations

Last observation: February 2022

So what do we see using the range of benchmarks in spring 2022? Similar to what we find using 2019 as the benchmark, we see strength across most indicators. Several measures are well above the top end of the range—importantly, those related to labour shortages. For other measures, most indicators are within the range of the different benchmarks and usually at the top end. Wage measures are more mixed.

The similarity between 2019 and 2022 suggests that the 2019 average coincided with a period of labour market strength—including when the LI gap is believed to have been closed. The 2019 average is in fact at the top of the range of many of the measures considered (**Chart 4**). Using the broader range of benchmarks supports the conclusion that labour market slack was largely absorbed in March 2022.[10]

Chart 4: The 2019 average is at the top of the range for many measures considered



Note: This chart presents the current value of labour market indicators when compared with their historical best and historical worst. Benchmarks are comprised of the Hamilton filter, the Hodrick-Prescott filter, the corresponding value of the indicator during a period when the labour input gap was closed and, for selected indicators, trend estimates produced by the Bank of Canada. Data for all series are from Statistics Canada's Labour Force Survey (LFS) unless otherwise noted. BOS is Business Outlook Survey; JVWS is Job Vacancy and Wage Survey.
*Vacancy rate data are from 2015 onward and may affect trend estimates.

Sources: Statistics Canada, Bank of Canada and Bank of Canada calculations

Last observations: LFS, February 2022; BOS, 2022Q1; JVWS, 2021Q4

Benchmarks need regular updates

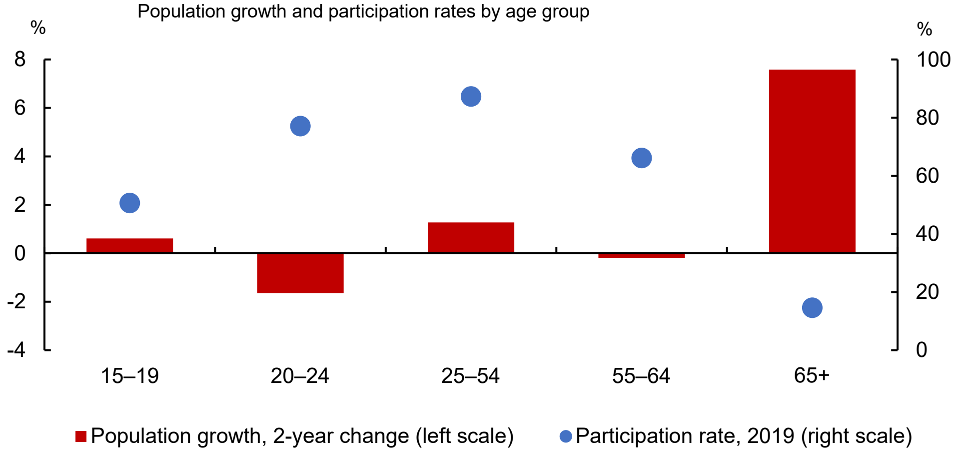
In addition to the use of ranges, given ongoing structural changes in the labour market, regular (annual) updating of benchmarks is *also* needed. The 2019 average is a useful benchmark for the Canadian labour market because it allows for a quick comparison with pre-pandemic conditions and because 2019 was a period with a strong labour market. However, the further we get from 2019, the less relevant this benchmark might become. One important consideration since 2019 has been shifting demographics. For example, **Chart 5** shows that the groups with the fastest population growth since 2019 are also less likely to participate in the labour market.[11] These shifts have implications for aggregate benchmarks such as the employment and participation rates.

[10] For certain measures, such as the vacancy rate, the 2019 average is unsurprisingly at the bottom of the range given the strength of vacancy rates observed during the recovery period. This results in higher trend estimates from the HP and Hamilton filters.

[11] Other structural changes that could also matter include the digitalization of the economy and policy changes.

Chart 5: Population growth has been strongest among older workers

Population growth and participation rates by age group



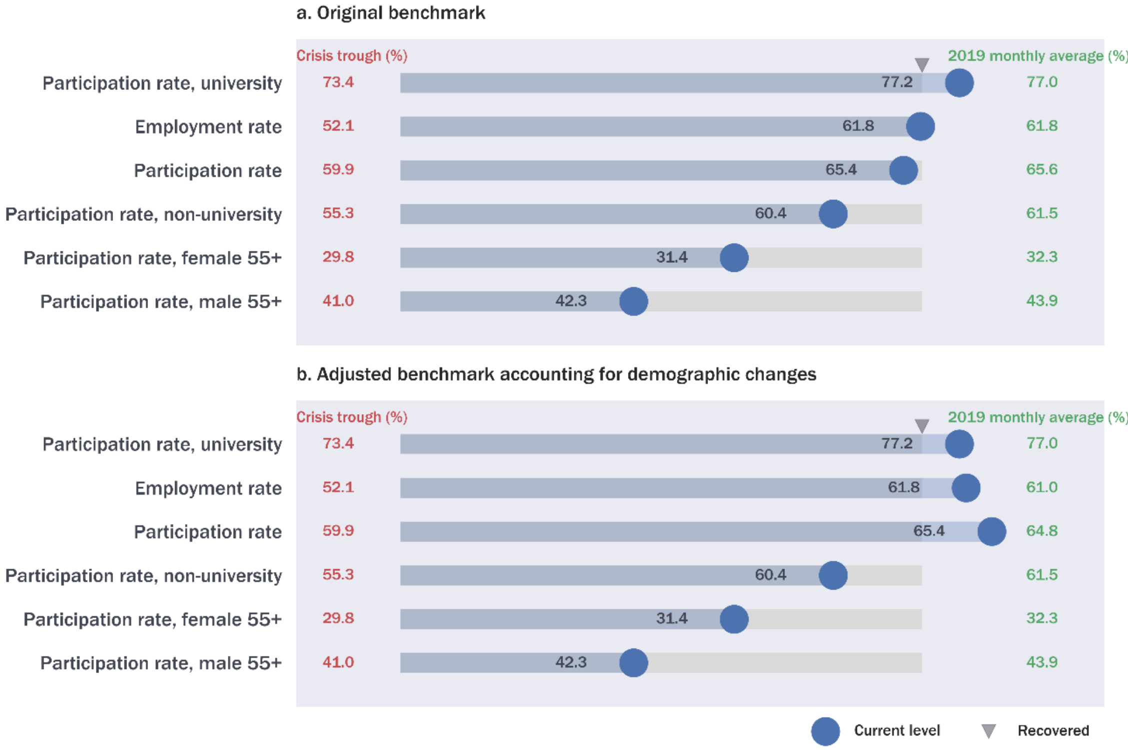
Sources: Statistics Canada and Bank of Canada calculations

Last observation: February 2022

Failing to account for this demographic shift would result in benchmarks that may not be consistent with maximum sustainable employment given the higher propensity of older workers, who are now greater in number, to retire and leave the labour market after age 65.

To account for this, we construct alternative 2019 benchmarks, which hold age-specific rates at 2019 averages but use current population shares to construct the aggregate benchmarks. Using these alternative benchmarks reduces the remaining gaps in employment and participation rates (**Chart 6**).

Chart 6: Adjusting benchmarks for demographic changes reduces gaps in employment and participation



Note: This chart illustrates the extent to which measures of labour market conditions have recovered. The recovery is shown through progress bars, where the current value of each measure (depicted by a blue circle) is compared with its crisis trough and a benchmark value (the 2019 monthly average, pre-pandemic). Halfway progress implies that the measure has recovered half of the trough-benchmark distance. Panel a (b) presents the progress bars for selected indicators when benchmarks are not adjusted (adjusted) for demographic changes. The classification "University" refers to individuals with a university degree, while "Non-university" refers to those with less than a university degree. Data for all series are from Statistics Canada's Labour Force Survey (LFS) unless otherwise noted.

Sources: Statistics Canada and Bank of Canada calculations

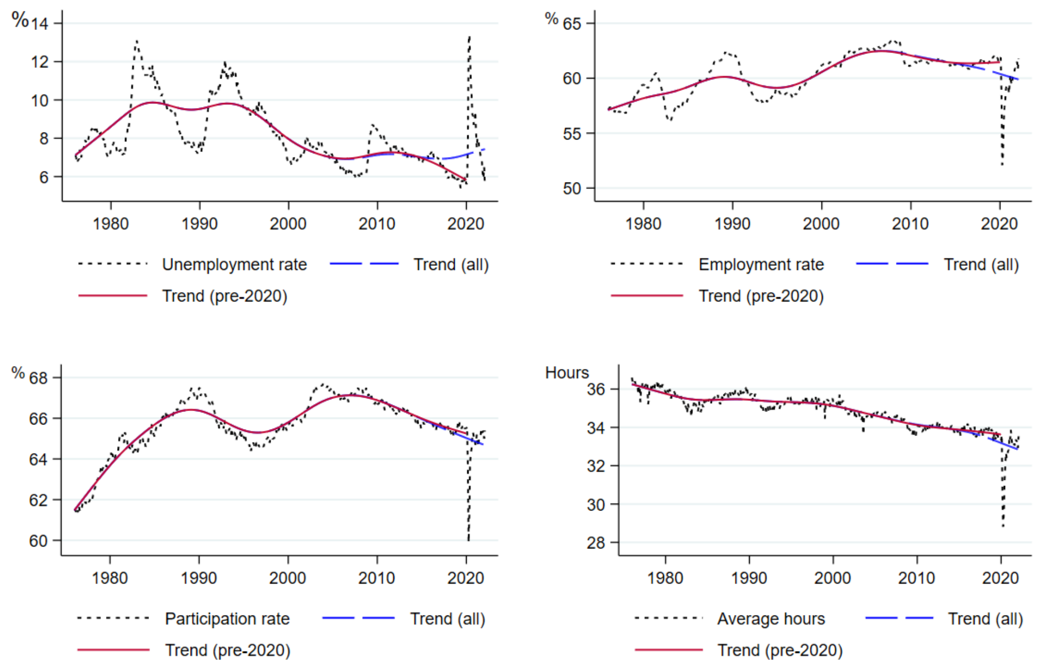
Last observation: LFS, February 2022

Regular updates to benchmarks would allow these demographic shifts to be incorporated. Since these are still gradual changes, annual updates would likely be sufficient to capture the evolution of structural factors.

Appendix A: Outsized effect of the pandemic on HP-filtered trend estimates

In this section, we highlight how the severe nature of the pandemic exacerbated the end-point issues that the HP filter is known to encounter. We conduct the following exercises. First, we apply the HP filter to the data up to February 2020 and obtain the trend component. Next, we apply the HP filter again, but on data that include the pandemic period. **Chart A-1** highlights our results. In the top left panel, the dramatic increase in the unemployment rate (dotted black line) during the pandemic causes the implied HP trend estimate (solid red line) to deviate from its downward trajectory as implied by the pre-2020 data (dashed blue line). Similarly, the severe impact of the pandemic accelerated the estimated trend decline in variables such as the employment rate, labour force participation rate and average hours worked, underscoring the outsized impact the pandemic has had on trend estimation. Because the pandemic may have led to significant changes in the allocation of labour resources, more data are required to verify whether the observed trends derived using the full data sample are signals of structural shifts or mere artifacts of the end-point problems associated with the HP filter.

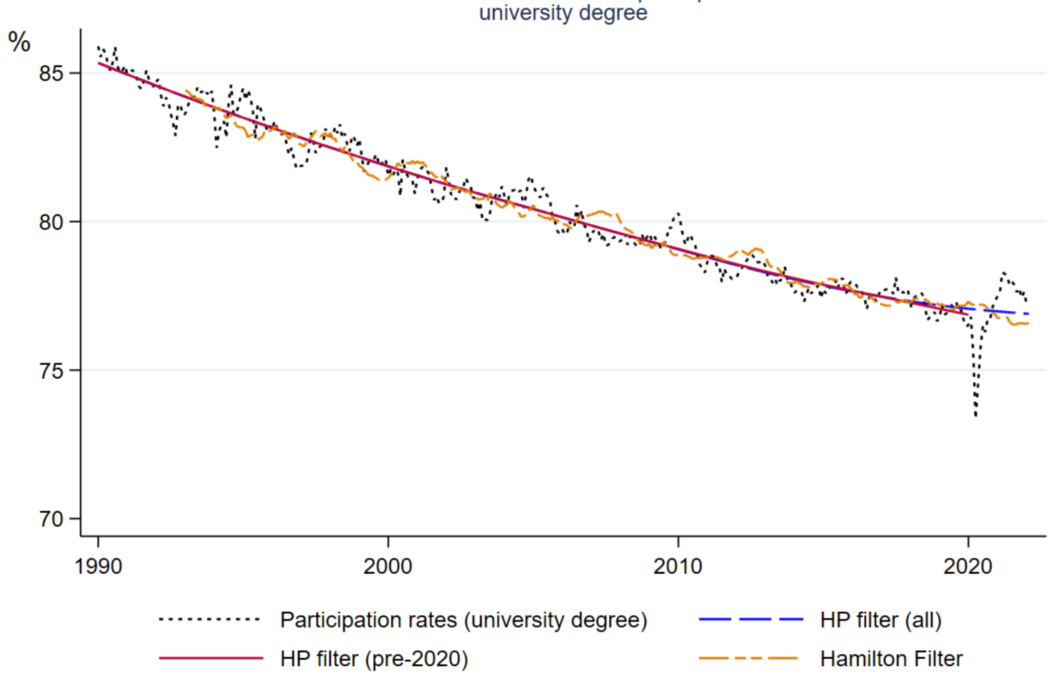
Chart A-1: Trend estimates differ when the pandemic is included



Sources: Statistics Canada and Bank of Canada calculations

Last observation: February 2022

Chart A-2: Trend estimates do not differ much for the participation rates of individuals with a university degree



Sources: Statistics Canada and Bank of Canada calculations

Last observation: February 2022

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