APPENDIX 1: CROSS-COUNTRY EVIDENCE

Section III of the working paper provides cross country evidence on the persistent effects of recessions. This appendix provides methodological details.

Methodology

We use standard local projection models (LPMs) to estimate the medium-term dynamics around recession episodes. LPMs involve estimating impulse responses to shocks by running separate regressions for each time horizon (h) of the form:

\[ Y_{i,t+h} - Y_{i,t-1} = \alpha_{i,h} + \beta_h REC_{i,t} + \gamma_h X_{i,t} + \varepsilon_{i,t} \quad (A1.1) \]

where \( REC_{i,t} \) is a dummy variable for the start of a recession taken from Martin et al (2015), \( X_{i,t} \) is a vector of control variables including lagged values of the recession dummy and lagged differences of the dependent variable, and \( \alpha_{i,h} \) are country fixed effects. The dependent variable represents changes over different horizons of our variable of interest, \( Y_{i,t} \).

For \( Y_{i,t} \), we use different variables, including log GDP and its various components: log of TFP, log of the capital stock, log of employment, the unemployment rate, and the labor force participation rate. Separate regressions are estimated for each variable.

The coefficient \( \beta_h \) directly estimates the impulse response for horizon h in response to a shock to the recession variable. Standard errors are clustered at the country level.

In our baseline specification we do not include year fixed effects. This is because the current crisis is a synchronized shock impacting all countries, therefore, to get context on how GDP and its components may respond to this crisis, excluding year fixed effects from the cross-country analysis is appropriate. We report robustness of our main result to including year fixed effects in Figure 4 of the main paper.

Sample

We focus attention on advanced economies as these are most comparable to Australia and New Zealand. Our exact country and time coverage is dictated by the availability of recession start dates.

In our baseline specification, we use recession start dates for 23 advanced economies as identified by Martin et al. (2015). The exact time coverage differs from country to country but broadly covers the period 1970 to 2012.
As a robustness check, we also use recession dates as identified by Dovern and Zuber (2020). This allows us to include a slightly broader country coverage (27 countries), though the time coverage is reduced to the period 1990 to 2017.

Data

Our specifications use data at the annual frequency. Data on our main dependent variables (GDP and its components) is taken from Penn World Table 9.1 (PWT) and the OECD. In particular, we take data for GDP, TFP, employment and capital stock from PWT. We supplement this with data on unemployment rate and labor force participation rate from the OECD.

In addition, we use data on crisis episodes by Laeven and Valencia (2018). We use this data to identify large recessions that were not accompanied by a banking or currency crisis i.e. recessions which did not have a banking or currency crisis a year before or after the start of the recession.
APPENDIX 2: ESTIMATION OF POTENTIAL OUTPUT BEFORE THE PANDEMIC

Section IV of the working paper provides estimates of potential output for Australia and New Zealand before the pandemic. This appendix provides methodological detail.

Methodology
The estimates of potential output presented in Figure 5 of Section IV are computed using a semi-structural multivariate filter model that incorporates a Phillips curve and Okun’s law.¹

The structure of the model can be summarized as follows. The output gap \( y_t \) is defined as the deviation of observable log real output \( Y_t \) from log potential output \( Y_t^* \).

\[
y_t = Y_t - Y_t^* \quad (A2.1)
\]

The dynamics of output can be defined by following three equations.

\[
Y_t^* = Y_{t-1}^* + G_t + \varepsilon_t^Y \quad (A2.2)
\]

\[
G_t = \theta G^ss + (1 - \theta) G_{t-1} + \varepsilon_t^G \quad (A2.3)
\]

\[
y_t = \Phi y_{t-1} + \varepsilon_t^y \quad (A2.4)
\]

The level of potential output evolves according to potential growth \( G_t \) and shock term \( \varepsilon_t^Y \), which can be interpreted as supply-side shocks. Potential growth is subjected to shock \( \varepsilon_t^G \), and converges to steady-state growth rate. Output gap follows AR (1) process and is also subject to shock \( \varepsilon_t^y \), which is interpreted as demand shocks.

The model also incorporates a (hybrid) Phillips curve, which links output gap to observable inflation.

\[
\pi_t = \lambda \pi_{t+1} + (1 - \lambda) \pi_{t-1} + \beta y_t + \varepsilon_t^\pi \quad (A2.5)
\]

where \( \pi_t \) denotes inflation.

In addition, the model employs the observed unemployment rate to help identify unobservable variables. Okun’s law links the output gap to the unemployment rate gap \( u_t \), the deviation of unemployment rate \( U_t \) from the nonaccelerating inflation rate of unemployment rate (NAIRU) \( U_t^* \).

\[
u_t = \gamma u_{t-1} + \delta y_t + \varepsilon_t^u \quad (A2.6)
\]

\[
u_t = U_t^* - U_t \quad (A2.7)
\]

¹ Discussion in this appendix is based on IMF (2015) and Blagrave et al. (2015). See Blagrave et al. (2015) for further details about the model.
Equation A2.6 is an Okun’s law relationship. In Equation A2.7, NAIRU $U_t^*$ is time-varying and follows:

$$U_t^* = \kappa U^{ss} + (1 - \kappa)U_{t-1}^* + \mu_t + \varepsilon_t^{U*} \quad (A2.8)$$

$$\mu_t = \eta \mu_{t-1} + \varepsilon_t^{\mu} \quad (A2.9)$$

where $U^{ss}$ denotes steady state unemployment rate, and $\mu_t$ denotes trend in NAIRU, which is subject to shock $\varepsilon_t^{\mu}$.

The estimation uses three observable variables: real GDP, inflation, and the unemployment rate. Annual data (1990-2019 for Australia, and 1995-2019 for New Zealand) are used for estimation, and parameters are estimated with Bayesian estimation techniques.\(^2\)

Estimated potential growth can be decomposed into underlying drivers, namely, capital, NAIRU, trend labor force participation rate, working age population, and total factor productivity, based on Cobb Douglas production function in Equation A5.1 in Appendix 5.\(^3\)

Figure 5 reports estimated potential growth rates before the pandemic for Australia and New Zealand and their decompositions.

---

\(^2\) Priors used in the estimations are reported in Blagrave et al. (2015).

\(^3\) Trend labor force participation rate is obtained by the Hodrick-Prescott filter with smoothing parameter $\lambda=100$. 
APPENDIX 3: PROJECTING MEDIUM-TERM GROWTH

Section IV of the working paper analyzes medium-term potential output for Australia and New Zealand. This appendix provides methodological details.

Growth Accounting Framework and Medium-term Projection

The paper employs growth accounting framework to analyze potential output in the medium term. The framework is based on the standard Cobb-Douglas production function augmented with detailed labor input items.

\[
\ln(Y_t^*) = \ln(z_t^*) + \alpha \ln(K_t) + (1 - \alpha) \ln(WAP_t \times LP_t^* \times (1 - U_t^*)) \quad (A3.1)
\]

where \(Y_t^*\) denotes potential output, \(z_t^*\) denotes cyclicality adjusted TFP, \(\alpha\) is the constant capital share of the economy (set as 0.4 both for Australia and New Zealand), \(K_t\) denotes capital level, \(WAP_t\) denotes working age population, \(LP_t^*\) denotes cyclicality adjusted labor force participation rate and \(U_t^*\) denotes Non-Accelerating Inflation Rate of Unemployment (NAIRU).

The medium-term projection is conducted in terms of the deviation from pre-COVID potential output projections, using potential output projections from the January 2020 World Economic Outlook data vintage as benchmark. First, the trajectory of each right-hand-side variable in the production function in Equation A3.1 is analyzed in terms of its deviation from pre-COVID projections. These deviations are then aggregated into a predicted revision of potential output from pre-COVID trends based on the Cobb-Douglas production function in Equation A3.1.\(^1\)

Figure 15 and 16 of Section IV show each component of potential output and potential output in deviation from pre-COVID projection. Figure 17 shows potential output under different scenarios in level.

\(^1\) Shocks on each variable are assumed to decay over the forecast horizon. In each year, sectoral reallocations are assumed to decay by 10 percent, debt overhang effects are assumed to decay by 20 percent, and uncertainty effects are assumed to decay by 50 percent.
Capital Accumulation

In the simulations above, capital accumulation is \( K_t \) is endogenously determined in line with growth theory. In the long-run, capital accumulation is assumed to follow a balanced growth path, where capital and output grow at same rate. Balanced growth path of capital is given as

\[
\Delta \ln (K^BGP_t) = \frac{\Delta \ln (z^*_t)}{1 - \alpha} + \Delta \ln (L^*_t) = \frac{\Delta \ln (z^*_t)}{1 - \alpha} + \Delta \ln (WAP_t \times LP^*_t \times (1 - U^*_t)) \quad (A3.2)
\]

where \( K^BGP_t \) denotes the capital level at balanced growth path, and \( L^*_t \) denotes cyclicality adjusted labor input, and \( \alpha \) denotes the constant capital share of the economy.

In the simulation, it is assumed that capital accumulation converges gradually to this balanced growth path.\(^2\) In addition, debt overhang effects and uncertainty effects discussed in Appendix 5 also affect the trajectory of capital accumulation.

\[
\ln (K_t) = (1 - \gamma) \ln (K^BGP_t) + \gamma \ln (K_{t-1}) + DO_t + U_t \quad (A3.3)
\]

where \( \gamma \) denotes persistence parameter (set at 0.66 both for Australia and New Zealand), \( DO_t \) denotes debt overhang effects and \( U_t \) denotes uncertainty effects, both discussed in Appendix 5.

Effects of labor reallocation on productivity

As discussed in Section IV, the pandemic has induced large sectoral reallocation. The simulations in this paper incorporate such effects of labor reallocation across sectors on productivity following Duarte and Restuccia (2010) and Goodridge et al. (2018). Following Goodridge et al. (2018), output growth can be decomposed into within-sector labor productivity growth, labor reallocation effects and aggregate labor inputs,

\[
\Delta \ln (Y^*_t) = \Delta \ln (LProd^{*,\text{within}}_t) + R^L_t + \Delta \ln (WAP_t \times LP^*_t \times (1 - U^*_t)) \quad (A3.4)
\]

where \( LProd^{*,\text{within}}_t \) denotes labor productivity growth within sectors, and \( R^L_t \) denotes labor reallocation effects on labor productivity. \( R^L_t \) captures effects of change in labor composition across sectors, which can be given as follows,

\[
R^L_t = \sum_{i=1}^{n} \frac{Lprod_{i,t-1}}{Lprod_{t-1}} \times \left( \frac{L_{i,t}}{L_t} - \frac{L_{i,t-1}}{L_{t-1}} \right) \quad (A3.5)
\]

\(^2\) Capital is assumed to adjust gradually due to adjustment costs. It is also implicitly assumed that capital level before the pandemic was on balance growth path.
where $L_{\text{prod}}_{t-1}$ denotes aggregate labor productivity, $L_{\text{prod}}_{i,t-1}$ denotes sector $i$’s labor productivity, $L_{i,t}$ denotes employment in sector $i$ and $L_t$ denotes aggregate employment. Reallocation effects are obtained with the change in employment share in sectors, multiplied by sector-level labor productivity in the previous period. It takes positive value if there is labor shift from a low-productivity sector to a high-productivity sector.

Figure 11 in Section III shows labor reallocation effects in Australia during the recession in 1990s and COVID-19 episode. In aggregate growth accounting in Equation A3.1, reallocation effects are included in total factor productivity.

---

3 Reallocation effects in the 90s calculated based on labor reallocation from 1990Q3 to 1993Q2, and reallocation effects after COVID-19 is calculated based on labor reallocation from March 14, 2020 to July 25, 2020 (weekly payroll data).

4 Jorgenson et al. (2007) show labor reallocation effects and capital reallocation effects (not considered in this paper) are included in change in aggregate total factor productivity. For New Zealand, labor reallocation effects in Australia is used, as the labor adjustment after the pandemic is masked by a large-scale wage subsidy program.
APPENDIX 4: SECTORAL REALLOCATION AND ITS EFFECT ON UNEMPLOYMENT RATE

Section IV of the working paper analyzes sectoral reallocation and the effects of shocks to sector allocation on the unemployment rate. This appendix provides methodological details.

**Sectoral Reallocation Index**

The degree of sectoral reallocation is analyzed using the method developed by Lilien (1982).\(^1\) Sectoral reallocation index is defined as the weighted standard deviation of sectoral differences, computed separately for the stock markets and labor markets:

\[
\sigma_t = \left[ \sum_{i=1}^{n} S_i (\Delta \ln x_{i,t} - \Delta \ln X_t)^2 \right]^{1/2}
\]  
(A4.1)

- For the stock market specification, \(S_i\) denotes the market capitalization share of sector \(i\), \(x_{i,t}\) denotes sectoral stock return at time \(t\), and \(X_t\) denotes the total stock market return at time \(t\). The index computes weighted standard deviation of sectoral stock returns, therefore quantifies sectoral dispersion at time \(t\). Sectoral stock prices are obtained from Financial Times Stock Exchange (FTSE) database. Data for 25 and 12 industries are used for Australia and New Zealand, respectively. The sectoral reallocation index is calculated at monthly frequency. Figure 8 in Section III and the left panel of Figure A4.1 display the estimated sectoral reallocation index for Australia and New Zealand.

- For the labor market specification, \(S_i\) denotes share of employment in sector \(i\), and \(x_{i,t}\) denotes sectoral employment at time \(t\), and \(X_t\) denotes the total employment at time \(t\). Data for 19 and 16 industries are used for Australia and New Zealand, respectively. The index is calculated at quarterly frequency.

Figure A4.1 shows sectoral reallocation indices estimated separately from stock markets and labor markets. For Australia, large sectoral reallocation is observed both in the stock market and the labor markets. For New Zealand, labor market-implied sectoral reallocation remains low in the second quarter, despite a sharp increase in the stock-implied sectoral reallocation.

index, as reallocation in labor market is masked by a large-scale wage subsidy scheme provided by the government.

Figure A4.1: The Speed of Economic Reallocation Across Sectors Is Unprecedented (Index of sectoral reallocation)

Effects of Reallocative Shocks

A simple structural vector autoregression model is employed to analyze the effects of reallocation shocks on the unemployment rate. The model is given as:

\[ y_t = \beta_0 + \sum_{k=1}^{m} \beta_k y_{t-k} + u_t \] (A4.2)

Where vector \( y_t \) includes the change in the unemployment rate and the sectoral reallocation index based on stock market returns obtained from Equation A4.1, \( \beta_k \) is the coefficient matrix on \( k \)th lag of \( y \), and vectors \( \beta_0 \) and \( u_t \) represent the constant terms and reduced-form error terms. The equation is estimated at monthly frequency for Australia using data over September 1995-May 2020, and at a quarterly frequency for New Zealand using data over 2000Q4-2020Q1, where unemployment rate is only available at quarterly frequencies. Number of lags are set at 12 for Australia, and 6 for New Zealand.

Following the literature (e.g. Campbell and Kuttner 1996, Tase 2019), sectoral reallocation shocks are identified, using Cholesky decomposition, such that they do not affect the unemployment rate contemporaneously. Figure 9 of Section IV reports cumulative impulse responses of unemployment rate changes to identified reallocation shocks scaled to the magnitude in COVID-19 episode.²

² Results are broadly unchanged if the change in terms of trade is included in the vector autoregression.
APPENDIX 5: EFFECTS OF DEBT OVERHANG AND UNCERTAINTY ON INVESTMENT

Section IV of the working paper analyzes effects of debt and uncertainty on firm-level investment behavior. This appendix provides methodological details.

Determinants of firm-level investment behavior

The following panel regression model, a Tobin’s Q model augmented with firm-level financial variables and uncertainty, is employed to analyze effects of debt and uncertainty on firms’ investment:

\[
\frac{I_{it}}{K_{i,t-1}} = \alpha + \tau_t + \delta_t + \beta X_{i,t} + \epsilon_{i,t} \quad (A5.1)
\]

where \(I_{it}\) denotes firm \(i\)’s capital expenditure at time \(t\), \(K_{i,t-1}\) denotes firm \(i\)’s capital stock, and \(X_{i,t}\) includes a set of firm-level variables. \(X_{i,t}\) includes the debt level (debt-to-asset ratio), firm-level uncertainty (measured as firm-level stock volatility), the cost of debt (interest rate expenditure-to-debt), liquidity (current-asset-to-current-liability ratio), and Tobin’s Q (measured as the sum of market value of equity and book value debt divided by book value of asset).1 The regression includes firm-level and time fixed effects, and firm-clustered robust standard errors are estimated. All explanatory variables are included with a one-year lag to preempt endogeneity issues. Firm-level data are of annual frequency, obtained from the IMF Corporate Vulnerability Unit Database, which is based on the Worldscope database. Firms in the financial sector are excluded from the sample and firm-clustered robust standard errors are estimated.

Estimated parameters on leverage and uncertainty are reported in Figure 12 of Section IV. Table A5.1 reports the comprehensive regression results.

**Table A5.1 Determinants of firm-level investment**

<table>
<thead>
<tr>
<th>Dependent Variable: Investment-to-Lagged Capital</th>
<th>Australia</th>
<th>New Zealand</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cost of Debt (-1)</td>
<td>-0.404***</td>
<td>-0.124</td>
</tr>
<tr>
<td></td>
<td>(0.097)</td>
<td>(0.171)</td>
</tr>
<tr>
<td>Debt (-1)</td>
<td>-0.213***</td>
<td>-0.157***</td>
</tr>
<tr>
<td></td>
<td>(0.027)</td>
<td>(0.046)</td>
</tr>
<tr>
<td>Liquidity (-1)</td>
<td>0.009***</td>
<td>0.013*</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.007)</td>
</tr>
<tr>
<td>Uncertainty (-1)</td>
<td>-0.037***</td>
<td>-0.069***</td>
</tr>
<tr>
<td></td>
<td>(0.012)</td>
<td>(0.034)</td>
</tr>
<tr>
<td>Tobin’s Q (-1)</td>
<td>0.019***</td>
<td>0.044***</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.007)</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.084</td>
<td>0.058</td>
</tr>
<tr>
<td>Sample Period</td>
<td>1994-2018</td>
<td>1990-2019</td>
</tr>
<tr>
<td>Number of Observation</td>
<td>7,893</td>
<td>1,443</td>
</tr>
</tbody>
</table>

Note: In the table, *** and * indicate statistical significance at 1 and 10 percent level, respectively. Time fixed effects and firm fixed effects are controlled.

---

1 Although theoretically Tobin’s Q is a sufficient statistic for investment under certain assumptions, other variables have commonly been found to have important additional explanatory power (Bond and Reenen, 2007).
Effects of debt overhang

To analyze the effects of rising debt due to COVID-19, first, the increase in debt is estimated using business survey data. Business survey data compiled by the Australian Bureau of Statistics provide information on revenue losses due to COVID-19 at the sectoral level (Figure A5.1).\(^2\) Based on firm-level data used for the above panel regression and sectoral information on revenue losses, the increase in debt level is projected using the following equation:

\[
\Delta D_{i,t} = \delta \ast (1 - T) \ast \frac{1}{4} \ast \{ S_{i,t}^{75\%} \ast (-.75) \ast R_{i,t-1} + S_{i,t}^{50\%} \ast (-.625) \ast R_{i,t-1} + S_{i,t}^{25\%} \ast (-.375) \ast R_{i,t-1} + S_{i,t}^{L25\%} \ast (-.125) \ast R_{i,t-1} \}
\]  

(A5.2)

where \( \Delta D_{i,t} \) denotes change in debt, \( T \) denotes effective corporate tax (which is set at 0.3 in the simulation), \( R_{i,t-1} \) denotes revenue in previous period, and \( S_{i,t}^{j} \) denotes share of firms in the sector that report revenue loss at range \( j \), \( \delta \) denotes elasticity of debt to revenue loss (set as 0.8, based on cross-country analysis by De Vito and Gomez, 2020).\(^3\)

Based on the projected firm-level increase in debt and sensitivity parameters obtained in Equation A5.1, firm-level debt overhang effects can be estimated as:

\[
\Delta (I/K)_{i,t} = \beta_{debt} \frac{\Delta D_{i,t}}{A_{i,t-1}}
\]  

(A5.3)

where \( \Delta (I/K)_{i,t} \) denotes the impact of debt on firm \( i \)’s investment (expressed as the change in its investment-to-capital ratio), \( \beta_{debt} \) denotes the regression coefficient on the debt level (debt-to-asset ratio) from Equation A5.1, and \( A_{i,t-1} \) denotes firm \( i \)’s total asset at previous period (\( \frac{\Delta D_{i,t}}{A_{i,t-1}} \) is estimated change in debt-to-asset ratio). Figure 13 of section III displays the

---

\(^2\) Business Impacts of COVID-19, June 2020 (5676.0.55.003).

\(^3\) The survey measures revenue losses at five ranges, namely 0-25 percent, 25-50 percent, 50-75 percent, and greater than 75 percent. In Equation A5.2, \( S_{i,t}^{j} \) is determined based on the sector the firm \( i \) belongs.
distribution of firm-level debt overhang effects for Australian firms. The aggregate level of
debt impact on capital accumulation is obtained using a weighted average of firm-level
impacts.4

Effects of uncertainty

Similarly, firm-level impacts of increased uncertainty can be obtained based on parameters
obtained in the panel regression in Equation A5.1. The impact of uncertainty is given as:

$$\Delta \left( \frac{I}{K} \right)_{i,t} = \beta_{\sigma} \Delta \sigma_t$$ (A5.4)

where $\Delta \left( \frac{I}{K} \right)_{i,t}$ denotes the uncertainty effect on firm $i$’s investment (expressed as the
change in the investment-to-capital ratio), $\beta_{\sigma}$ denotes the regression coefficient on
uncertainty (firm-level stock volatility), and $\Delta \sigma_t$ denotes the change in uncertainty. Due to
data limitations, we calculate the aggregate level change in uncertainty based on
S&P/ASX200 VIX index and apply that to firm-level uncertainty.5 Therefore, aggregate level
effects are also obtained by Equation A5.4.

---

4 For New Zealand, we assume aggregate debt effects similar to Australia due to data availability issues. In
doing so, difference in parameters reported in Table A5.1 is adjusted.
5 Due to limited data availability, change in S&P/ASX200 VIX is also applied to New Zealand data.
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