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Botha, Ferdi; de New, John P.; de New, Sonja C.; Ribar, David C.; Salamanca, Nicolás

# Working Paper COVID-19 labour market shocks and their inequality implications for financial wellbeing

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# COVID-19 labour market shocks and their inequality implications for financial wellbeing

Ferdi Botha<sup>a,b</sup>, John P. de New<sup>a,b,c,1</sup>, Sonja C. de New<sup>b,d,e,g</sup>, David C. Ribar<sup>a,f,g</sup> & Nicolás Salamanca<sup>a,b,g</sup>

<sup>a</sup> Melbourne Institute: Applied Economic & Social Research, University of Melbourne
 <sup>b</sup> ARC Centre of Excellence for Children and Families over the Life Course, Australia
 <sup>c</sup> Global Labor Organization (GLO), Bonn, Germany
 <sup>d</sup> Centre for Health Economics, Monash University, Melbourne
 <sup>e</sup> RWI Research Network, Essen, Germany
 <sup>f</sup> Department of Economics, Georgia State University, Atlanta
 <sup>g</sup> Institute of Labor Economics (IZA), Bonn, Germany

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## Abstract

Using an online survey of Australian residents, we elicit the potential impacts of COVID-19 related labour market shocks on a validated measure of financial wellbeing. Experiencing a reduction in hours and earnings, entering into unemployment or having to file for unemployment benefits during the pandemic are strongly and significantly associated with decreases in financial wellbeing of 29% or 18 points on the financial wellbeing scale of 0-100, despite various government measures to reduce such effects. Unconditional quantile regression analyses indicate that the negative COVID-19 labour market effects are felt the most by people in the lowest percentiles of the financial wellbeing distribution. Counterfactual distribution regressions indicate a shifting of the financial wellbeing distribution leftwards brought on by those suffering any of the above-mentioned labour market shocks, indicating potential significant increases in financial wellbeing disadvantage and inequality.

#### JEL Classification: D14; D39; J65; G51; D63

Keywords: Financial wellbeing, COVID-19, unemployment, earnings reduction, inequality

<sup>&</sup>lt;sup>1</sup>Corresponding author: Prof Dr John de New, Melbourne Institute, University of Melbourne, 111 Barry Street, Carlton VIC 3053, Australia; johnhd@unimelb.edu.au; Tel: +61-3-9035-8311. The authors thank Tom Wilkening and Jack Rejtman for feedback on the survey and the anonymous respondents recruited from Facebook, Twitter and Instagram. Special thanks to Justin Wolfers, the UK Understanding Society Survey, RWI-Essen, LCC, Lynn Wilson at UofT, Sue Dynarski, Shoshana Grossbard, John Holbein, Scott Cunningham and many others for publicising the survey at the beginning.

## 1. Introduction

The COVID-19 pandemic has spawned a once-in-a-century international health and economic crisis. Nations racing to slow the spread of the virus have imposed lockdowns and social distancing measures, which have shuttered businesses, forced people out of work, and decimated incomes. The World Bank (2020) projects that the global economy will contract by 5.2 percent. While aspects of the macroeconomic consequences have been carefully considered, we know much less about the extent to which the crisis is affecting individuals' financial wellbeing or how people are coping financially. Job and earnings losses are undoubtedly harmful to financial wellbeing, but the size of the impacts is uncertain because myriad factors, including people's financial reserves and financial behaviour, government assistance, and social resources provide ways of mitigating the effects.

In this paper, we investigate how labour market shocks, as a direct result of COVID-19, are associated with the financial wellbeing of Australians. We are specifically interested in the relationship with *financial wellbeing*, rather than income alone. Financial wellbeing can range widely within income levels and is arguably a more direct measure of people's enjoyment of their income, their consumption, and their financial worries and constraints. Focusing on financial wellbeing gives us a better picture of the true pressures felt by all individuals across the income and wealth distribution during the pandemic.

Financial wellbeing as a validated multi-item measure is a relatively new concept, that we developed in previous research to capture the extent to which individuals feel that they are able to meet their financial obligations, to have the financial freedom to enjoy additional consumption and other fulfilling choices, to control rather than be controlled by their finances, and to have security and be free from financial anxiety, now, in the future and under possible adverse circumstances. Our validated measure captures functional, situational as well as temporal components, and while it is related to objective financial indicators, it is a distinct concept as we show in Comerton-Forde et al. (2018).

As one of the first studies of its kind, we use unique survey data collected during the intense period of the Coronavirus pandemic in Australia between March and July 2020, which contained the validated financial wellbeing instrument as well as a set of demographic information, and in particular questions around individuals' labour market experience during the pandemic. This allows us to study people's financial wellbeing associated with labour market shocks following from COVID-19 restrictions in Australia.

Labour market shocks such as unemployment, reduced work hours and wages are likely to affect financial wellbeing through three main channels. First, such shocks likely reduce current and permanent income, and this might impact financial wellbeing. Previous research has found associations between income or wealth and financial satisfaction (Bonke and Browning, 2009; Brown and Gray, 2016), financial hardships (Shim et al., 2009) as well as financial wellbeing (Comerton-Forde et al., 2020). Second, negative labour market shocks could reduce creditworthiness and borrowing ability, which would reduce the scope for financial behaviour and impact financial wellbeing (French, 2018). Third, labour market shocks could have adverse psychological effects, which might influence financial wellbeing, such as through loss of control (Vlaev & Elliott, 2014) and increased stress (Netemeyer et al., 2017). In line with this, Botha and de New (2020) show a negative association of COVID-19 related unemployment with subjective wellbeing.

Consistent with these mechanisms, research has found direct associations between unemployment and several financial outcomes, including financial satisfaction (Bonke & Browning, 2009; Brown & Gray, 2016; and Simona-Moussa & Ravazzini, 2019), difficulties managing financially (French, 2018), and financial hardships (Scutella & Wooden, 2004). Only two studies have investigated the effects of adverse labour market outcomes using comprehensive, summative measures of financial wellbeing. Brenner et al. (2020) found a negative association between unemployment and the U.S. Consumer Finance Protection Bureau (CFPB) scale of financial wellbeing (CFPB, 2017), and Comerton-Forde et al. (2020) found a similar relationship using the Melbourne Institute-Commonwealth Bank of Australia Reported Financial Wellbeing Scale (Comerton-Forde et al., 2018). However, both of these studies examined joblessness in the context of a robust economy and not in the midst of a global crisis.

Between March 10 and July 30, 2020, Australia has had 16,303 recorded coronavirus infections and 189 deaths. At its first peak on March 28, Australia recorded 458 new infections. Later in the second peak on July 30, daily new infections reached 721. The Australian labour market was profoundly hit by the imposed measures to restrict the outbreak. Starting on March 23, around the peak of the first wave of the coronavirus crisis in Australia, non-essential

businesses, including bars, cinemas, religious facilities, casinos and gyms, were closed. Several days later many shops began to close and stand down staff. The demand for welfare payments was so high, that the website of the Australian government agency responsible for welfare payments, *Centrelink*, crashed. In the following days, starting March 26 further businesses had to close: restaurants, cafes, food courts. A second wave of COVID-19 infections started at the end of June affecting the state of Victoria only. As such by July 30, 2020, dramatic state-wide emergency plans in Victoria were installed requiring stay-at-home unless going to get medical help, getting supplies, going to a workplace where the work could not be done at home, and caregiving.

The various impacts on Australian businesses are reflected in the official labour market statistics in Figure A1. The unemployment rate increased by 2.2%-points from 5.2% in March to 7.4% in June. The government introduced a wage subsidy (*JobKeeper*), which kept people officially in employment albeit with significant reductions in wages and hours worked. If we group these underemployed individuals, who would prefer to work more hours than are currently available to them, together with the unemployed, this underutilisation rate is much higher at 19.1% in June. The demand for welfare benefit payments, as proxied by the Google search frequency for *Centrelink* increased by 213% between February and March.

Our study finds that labour market shocks directly related to COVID-19 are associated with substantial and significant declines in financial wellbeing, not just on average, but in particular at the lower end of the financial wellbeing distribution. Distribution regressions suggest large potential gains in equality in financial wellbeing if one were to counterfactually remove the negative associations of COVID-19 labour market shocks with financial wellbeing across the distribution.

# 2. The COVID-19 and YOUR Wellbeing Survey

The data for our analyses were collected in April through July 2020 using a customised Qualtrics survey, *COVID-19 and YOUR Wellbeing*.<sup>2</sup> The survey asked about many outcomes relevant to the crisis, including personal events experienced due to COVID-19, financial wellbeing, subjective wellbeing, and mental health. Participants were recruited via social

<sup>&</sup>lt;sup>2</sup> This was an internet-based survey carried out at the University of Melbourne, Australia, led by the chief investigator John de New. Ethical approval for the project was obtained from the University of Melbourne (Australia) Human Research Ethics Committee (Approval ID: 2056701.1).

media, mainly via advertisements placed on social media. The final analysis sample as of July 7, 2020 includes 2,325 Australian residents who indicated that they were at least 18 years old. To make the sample representative of the general Australian population, we apply population weights based on age and gender population data available from the Australian Bureau of Statistics (ABS, 2019).

#### 2.1 Financial wellbeing

Financial wellbeing has been defined many ways in previous research. We follow Comerton-Forde et al. (2018:6) and define financial wellbeing as 'the extent to which people both perceive and have (i) financial outcomes in which they meet their financial obligations, (ii) financial freedom to make choices that allow them to enjoy life, (iii) control of their finances, and (iv) financial security – now, in the future, and under possible adverse circumstances.' From this definition, Comerton-Forde et al. (2018) developed a 10-item scale of self-reported financial wellbeing and demonstrated the validity and reliability of the measure. Botha et al. (2020) derived an abbreviated 5-item version of the scale and showed that it performs very similarly to the original 10-item scale. To keep the total survey length to 10 minutes, the COVID-19 and YOUR Wellbeing Survey used the 5-item scale.

Figure 1 shows for each of the underlying subcomponents of financial wellbeing the proportion of people who selected each answer per subcomponent (the grey bars). The orange line shows how the subcomponents relate to the overall financial wellbeing measure: it graphs the average financial wellbeing score for everyone who selected each of the respective response options of each of the 5 items. The items cover current and future dimensions of financial wellbeing. Items 1, 3, and 4 relate to respondents' immediate day-to-day financial outcomes; item 2 relates to maintaining future financial wellbeing during unexpected events; and item 5 relates to sustaining financial wellbeing over time and reaching long-term financial goals.

Botha et al. (2020) reported results from factor analyses that showed that all five items load on a single factor. The financial wellbeing scale is obtained by simply summing the five items and multiplying the sum by five to obtain a financial wellbeing score that ranges from 0 (low financial wellbeing) to 100 (high financial wellbeing); this scale has a reliability coefficient of

0.91.<sup>3</sup> Across all subcomponents, a significant portion of people report low financial wellbeing. For example 15% report that they cannot enjoy life at all or very little because of the way they are managing their money, 25% could not handle a major unexpected expense at all or very little, 17% do not feel on top of their finances, 19% are not comfortable with their current level of spending and 31% report not to have enough money to provide for their financial needs in the future.

# < Figure 1 here >

#### 2.2 Covariates

The core explanatory variables for our analyses relate to events *specifically because of COVID-19.* We ask: "Regarding the world-wide Corona Virus COVID-19 pandemic, there have been many far-reaching economic and social implications, even if you or your family does not have the virus. *Because of COVID-19, since Dec 1, 2019* have you experienced any of the following (may choose multiple):

- Reduced Work Hours
- Reduced Wage/Salary
- Loss of employment or business closure
- Filed for Unemployment Benefits/Insurance/Assistance"

The terminology of "benefits" has been kept purposefully generic to be applicable world-wide; however, in Australia, these benefits relate specifically to "JobSeeker" government programs (a minimal non-means-tested unemployment assistance) and are a fixed base amount paid fortnightly.<sup>4</sup> We combine the shocks of salary reduction and hours worked reduction to reflect the nature of the Australian "JobKeeper" population (short time work benefits for those officially still classified as "employed", but facing reduced industry demand and potentially not actually working).<sup>5</sup> We combine the shocks of entry into unemployment or applying for benefits to reflect the Australian "JobSeeker" population.

<sup>&</sup>lt;sup>3</sup> Botha et al. (2020) also estimated an Item Response Theory (IRT) graded response model with the five items. The IRT results show that each item has similar discrimination and that a summative scale is appropriate. The Spearman correlation between the summative scale and the latent predicted score from the IRT model is 0.996 suggesting that the simple summation financial well-being index is highly correlated with the latent financial wellbeing score.

<sup>&</sup>lt;sup>4</sup> See https://treasury.gov.au/coronavirus for further details.

<sup>&</sup>lt;sup>5</sup> Of the 35% who experience either a salary reduction or a reduction in work hours, the vast majority of this subgroup (74.3%) experienced both shocks simultaneously due to COVID-19. Rather than investigating the

We consider the association with financial wellbeing of each of the two labour market shocks, and also of whether a person has experienced *either* of these shocks. Additional demographic controls include the respondent's age group, gender, occupation field, household size and Australian state, and a linear time trend. Given the 10-minute response limit of the online survey, elicitation of additional demographic information was not possible.

Table A1 reports the descriptive statistics on the main variables used in this paper. Mean financial wellbeing is roughly 61.5 on the 0-100 scale. About 26% of respondents experienced a reduction in working hours and salaries, whereas about 22% experienced job loss and/or had to apply for unemployment benefits. Almost 32% of Australians experienced at least one labour market shock. Table A2 shows that the labour market impacts of the pandemic seem to be felt across all demographic groups, but especially by women, the young, those in larger households (likely families with several children) and those working as sales workers and labourers.

Figure 2 depicts the factual distribution of financial wellbeing as observed and for the "treated"; those who experienced any COVID-19 labour market shock. The largest mass of the observed distribution is between 55 and 75 on the financial wellbeing scale of 0-100.<sup>6</sup> This picture changes dramatically for the distribution for the treated only, with its mass situated much further to the left.

# < Figure 2 here >

#### 3. Empirical Strategy

#### 3.1 Average associations

First, we estimate standard linear models for financial wellbeing in which we regress financial wellbeing, *FWB*<sub>it</sub>, on each of the COVID-19 related labour market shocks, *Shock*<sub>it</sub>, in separate regressions:

impact of two shocks separately, that affect mostly the same population, we focus on the subgroup of people who experienced both of those shocks, which is reflective of a clear economic disadvantage and comprises people who would qualify for JobKeeper.

<sup>&</sup>lt;sup>6</sup> There is a surprising spike at 100 on the 0-100 score. This could potentially indicate a positive self-selection of people taking part in the survey.

$$FWB_{it} = \alpha + \beta Shock_{it} + \gamma_1 Demog_{it} + \gamma_2 LabMkt_{it}$$

$$+ \gamma_3 S_{it} + \gamma_4 TimeTrend_t + \varepsilon_{it}$$
(1)

where *Shock*<sub>*it*</sub> represents a single COVID-19 related shock, namely (a) having experienced a reduction in earnings and hours worked, (b) entry into unemployment or having filed for unemployment benefits, or (c) having experienced either shock (a) or (b);  $Demog_{it}$  represents age, gender and household size indicators;  $LabMkt_{it}$  represents employment status and occupation dummies;  $S_{it}$  is a set of dummies for the Australian states or territories;  $TimeTrend_t$  is a linear time trend by week of the year, and  $\varepsilon_{it}$  is an error term. Our estimate of interest,  $\hat{\beta}$ , captures the financial wellbeing gap between otherwise similar people who did and did not suffer from a COVID-19 related labour market shock.

Whilst the extent and depth of COVID-19 shocks were hardly correctly predicted by anyone in Australia in early 2020, simply by the nature of people's observable characteristics such as occupation, age and gender, some people are more susceptible to suffer the labour market consequences. Financial wellbeing could also differ across these characteristics, which could create a bias in our estimates. To the extent that we control for these characteristics,  $\hat{\beta}$  reflects financial wellbeing gaps net of these biases. Still, other unobservable characteristics might make certain groups more at risk of experiencing a COVID-19 related labour market shock while at the same time impacting their financial wellbeing. Because of this, we cannot interpret  $\hat{\beta}$  as causal effects in equation (1), yet we still think of it as an informative statistic. Strong negative associations between COVID-19 related labour market shocks and financial wellbeing, indicate that either financial wellbeing is so low because of the shock (a causal pathway), or it indicates that those most exposed to COVID-19 labour market shocks are also exposed to other factors that decrease their financial wellbeing. Either way, it points to substantial inequalities in the experience of the pandemic, in terms of the experienced impact or exposure to labour market shocks by those who are already "doing it tough". Our estimates will likely capture both mechanisms and in the following section we investigate the extent to which our data allow us to disentangle the causal impact from the effect of exposure to other factors we do not observe.

#### 3.2 Estimate Bounds

Given the parsimonious nature of the short 10-minute survey, we can only control for a limited number of socio-demographic indicators such as occupation, age and gender. This leaves open the possibility of omitted variable bias. For example, it is possible that lower ability individuals disproportionately suffer the labour market burden of COVID-19, while also already experiencing lower financial wellbeing.

Thus, we also test the sensitivity of our results of the associations of COVID-19 labour market shocks with financial wellbeing by calculating bounds for the estimates of the  $\beta$  coefficient in equation (1). We implement the Altonji et al. (2005) and Oster (2019) calculations.<sup>7</sup> For a coefficient of negative value, the lower bound  $\beta_0$  is calculated on the basis that the proportional degree of selection on unobservables to selection on observables is 0 ( $\delta = 0$ ) and is therefore equivalent to our linear estimate for  $\beta$ , while the upper bound  $\beta_1$  is calculated on the basis that the amount of selection on unobservables is equal to selection on observables ( $\delta = 1$ ). This is a reasonable upper bound under two assumptions. The first assumption is that the number of observables and unobserved determinants of financial wellbeing is relatively large; this is likely to hold in our case since there are many determinants of financial wellbeing and any one survey can only measure a few. The second assumption is that the observables chosen act as a "random sample" of all determinants of financial wellbeing. This assumption is more contentious in our case since our survey was tailored to measure shocks likely to affect financial wellbeing (among other outcomes). Yet in our empirical design we did not actively choose measures that were good predictors of financial wellbeing (such as those included in the conceptual framework or empirical analyses of Comerton-Forde et al. 2020). Our chosen covariates are standard in most micro-econometric analyses of labour market outcomes and, to that extent, they can also be considered as a reasonably random sample of the determinants of financial wellbeing. We therefore take the view that unobservables should not be more important than our chosen observables in our analyses, lending validity to our bounding exercises. We also report the amount of selection on unobservables, relative to selection on observables, for the estimated effect to become insignificant.

### 3.3 Quantile Effects

<sup>&</sup>lt;sup>7</sup> Emily Oster provides a Stata ADO file called "psacalc.ado" which provides the unobservables/observables factor  $\delta$  and upper bound  $\beta$  estimations after an OLS regression.

Whilst the above regressions provide estimates of average associations of the  $Shock_{it}$  variables with  $FWB_{it}$ , one cannot immediately rule out *substantial* distributional associations. If one is already low in the  $FWB_{it}$  distribution, those suffering any number of COVID-19 related shocks will likely have a larger decrease in financial wellbeing than average or even than someone with higher initial levels of financial wellbeing. For targeted policies to help the most unfortunate, the relationship in the left tail of the financial wellbeing distribution should receive special attention.

To address this, we also estimate quantile regressions for  $FWB_{it}$  to determine whether the association between COVID-19's labour market shocks and financial wellbeing is different across the  $FWB_{it}$  distribution. We produce *unconditional* quantile estimates introduced by Firpo, Fortin, and Lemieux (2009), which have the interpretation of the size of the association at a given point in the  $FWB_{it}$  distribution.<sup>8</sup>

#### 3.4 Counterfactual distributions

Given that we identify differential associations of the  $Shock_{it}$  variables over the  $FWB_{it}$  distribution, we are interested to know what the  $FWB_{it}$  distribution would have counterfactually looked like, had these individuals not experienced  $Shock_{it}$ . Is the experience of  $Shock_{it}$  associated with a change in the  $FWB_{it}$  distribution? Is the  $FWB_{it}$  distribution more unequal due to its association with COVID-19 unemployment shocks  $Shock_{it}$ ?

To address these questions, our final analyses implement distribution regressions (see Chernozhukov et al. 2013, 2020a; Chernozhukov et al. 2020b; and Van Kerm 2015 for further details on distribution regression).<sup>9</sup> We start with the original OLS regression in (1), with the same regressors:

$$FWB_{it} = \alpha + \beta Shock_{it} + \gamma_1 Demog_{it} + \gamma_2 LabMkt_{it} + \gamma_3 S_{it}$$

$$+ \gamma_4 TimeTrend_t + \varepsilon_{it}$$
(1)

<sup>&</sup>lt;sup>8</sup> We use Fernando Rios-Avila's code contained in the Stata ADO "rifhdreg.ado", which calculates re-centered influence function regression.

<sup>&</sup>lt;sup>9</sup> We provide a complete DiNardo et al (1996) analysis in the Online Appendix B, treating the FWB as a continuous variable rather than a variable that contains discrete values as in the distribution regressions. The conclusions are consistent with those of the distribution regressions.

and replace the outcome variable  $FWB_{it}$  with a series of dummy variables  $fwbR_{it}$  such that:  $fwb0_{it} = 1 \ if \ FWB_{it} > 0 \ (and, 0 \ not),$   $fwb5_{it} = 1 \ if \ FWB_{it} > 5 \ (and, 0 \ not), \dots,$   $fwbR_{it} = 1 \ if \ FWB_{it} > R \ (and, 0 \ not), \text{ for } R = 10, 15, \ 20, \dots, 90$  $fwb95_{it} = 1 \ if \ FWB_{it} > 95 \ (and, 0 \ not).$ 

Thus, for the 21 discrete values of  $FWB_{it}$ , we estimate 20 separate linear probability models and obtain a separate estimate for the regressors for the dependent variable being greater than the threshold *R* in question, as in:

$$fwbR_{it} = \alpha + \beta Shock_{it} + \gamma_1 Demog_{it} + \gamma_2 LabMkt_{it} + \gamma_3 S_{it}$$
(1')  
+  $\gamma_4 TimeTrend_t + \varepsilon_{it}$ 

for each financial wellbeing threshold R = 0, 5, 10, ..., 95.

An interesting property of (linear) distribution regression is that summing up the respective linear probability model coefficients over the entire  $FWB_{it}$  distribution gives *exactly* the overall OLS estimate in (1), but we see the influence of the explanatory variables at *every point* in the outcome variable distribution.<sup>10</sup>

Distribution regression gives us an idea of the *magnitude* of the association at a particular value in the distribution of the outcome variable, but weighted by the corresponding mass of observations. For example, there could be much smaller effects in the middle of the distribution of financial wellbeing, but if far more people are sitting at these points in the distribution, the overall influence of these effects may be the greatest. Distribution regressions allow us to quantify these effects.

Distribution regressions also allow us to simulate a counterfactual distribution for the treated. Thus for those individuals who experienced a COVID-19  $Shock_{it}$ , we can calculate (1) an observed distribution of financial wellbeing, and (2) a counterfactual distribution of financial

<sup>&</sup>lt;sup>10</sup> It is slightly more complicated than that. There are 21 discrete values of FWB between 0 and 100 (in steps of 5), but 101 distinct values. Thus, the regression for *fwb0* and *fwb1*, ..., *fwb4* are all identical. Similarly, this holds for *fwb5* and *fwb6*, ..., *fwb9*, and so on (in groups of 5). The summation of *all* the coefficients for *fwb0*,1,2,3,4, ..., 99 is required to give the identical results as that of the standard OLS estimate.

wellbeing, in which we remove the association with  $Shock_{it}$  throughout the financial wellbeing distribution. For the treated, observed, and counterfactual distributions, we calculate the Gini inequality coefficient, the values of financial wellbeing at the median, the 10<sup>th</sup> percentile and the 90<sup>th</sup> percentile as measures of inequality in financial wellbeing.

## 4. Results

# 4.1 Average effects and effects over the distribution

The main regression results of the estimates of interest are presented in Table 1.<sup>11</sup> We report the linear estimates in Panels 1A-1C, column (1), that show the average association of the COVID-19 labour market shocks with financial wellbeing. In addition, to examine the associations of COVID-19 labour market shocks over the distribution of financial wellbeing, the unconditional quantile regression estimates for financial wellbeing at the 10<sup>th</sup>, 25<sup>th</sup>, 50<sup>th</sup>, 75<sup>th</sup> and 90<sup>th</sup> percentiles are reported in columns (2)-(6). In all estimations we control for demographic characteristics, labour market status and occupation as well as region fixed effects and a week of the year time trend.

Considering the linear results, having experienced a labour market shock of any type is associated with significantly lower levels of financial wellbeing. Having had, for example, a reduction in salary and working hours is related to an 18.8-point decrease in financial wellbeing (0 to 100) relative to people who did not experience such a shock. This is equivalent to levels of financial wellbeing reduced by 31% compared to the mean of 61.5. Having been made redundant or having been forced to apply for unemployment benefits is associated with a similar 15.8-point drop in financial wellbeing (reduction of 26%). Having experienced either shock is associated with a 17.9-point decrease in financial wellbeing (reduction of 29%). It is worth noting that in these COVID-19 crisis times, having experienced reductions in salary and hours worked is statistically equivalent to the shock of unemployment due to COVID-19. All three scenarios are statistically identical in the magnitude of the associated shock, so we will focus here primarily on the results for "any shock".

Using the Altonji et al. (2005) and Oster (2019) calculations, and maintaining their two-part assumption, we place an upper bound of the estimated associations at the mean. For example,

<sup>&</sup>lt;sup>11</sup> Only the coefficients of the relevant labour market shock indicators are reported in Table 2. The full regression results for any COVID-19 shocks are reported in Table A3.

on average, having a direct COVID-19-related reduction in salary is associated with a drop in financial wellbeing of 18.8 points on the 0-100 scale. Using the Altonji et al. (2005) and Oster (2019) calculations and assuming a  $R_{max} = 1.3(R^2)$ , where  $R^2$  is from the OLS regressions with all controls, we place an upper bound of the effect at -15.9 points when assuming that selection on unobservables is equal to that of observables. Selection on the unobservables would have to be 2.77 times higher than that on the observables to render the reduction in salary and hours coefficient insignificant (Table 1, Panel 1A). As this calculation depends on the chosen  $R_{max}$  as well as the included control variables, it only gives us an indication about the potential role of unobservables, but it is reassuring that all upper bounds of the negative coefficients are well below zero and that proportional selection on the unobservables to render the estimated coefficients insignificant. At a minimum, we cannot rule out that the estimated effects include at least partly causal effects running from a shock to a reduction in financial wellbeing.

# < Table 1 here >

Although the average associations of financial wellbeing with COVID-19 labour market shocks are large, these linear estimates at the *mean* obscure important differences *across* the financial wellbeing distribution. Specifically, examining the entire financial wellbeing distribution, in the quantile regression results (Table 1, Panels 1A-1C, columns (2)-(6)), labour market shocks have a much larger association with financial wellbeing of individuals in the lower parts of the financial wellbeing distribution, especially the 10<sup>th</sup> and 25<sup>th</sup> percentiles. The relationship between labour market shocks and financial wellbeing for those in the 90<sup>th</sup> percentile is significant and negative, yet at around a third of the magnitude as in the left tail of the distribution. The negative associations of labour market shocks with financial wellbeing distribution.

In Table 1, Panel 1A for example, the association with a *salary reduction* is strongest for the 25<sup>th</sup> percentile with a drop of 30.7 points, whereas the 75<sup>th</sup> percentile experiences only a 14.3-point drop for the same shock. This is likely due to the larger degree of asset income in the total portfolio of income sources of those in the 75<sup>th</sup> percentile, as opposed to the 25<sup>th</sup> percentile relying predominantly on earnings income of wages and salary. Furthermore, the type of salary reduction may vary systematically over the distribution: those particularly well off may experience a salary reduction that affects bonuses or premiums, whereas the lower 25% may

be affected by more binding reductions in their base or regular salaries. Overall the estimated associations are surprisingly similar for experiencing a reduction in salary and hours (Panel 1A) compared to unemployment and having to apply for benefits (Panel 1B), as well as having experienced any shocks (Panel 1C). Appendix Figure A2 shows the estimated coefficients of having experienced *any shocks* (Panel 1C) of the unconditional quantile regression at various slices of the financial wellbeing distribution as well as at the linear estimate graphically.

To ascertain whether the inter-percentile differences of experiencing COVID-19 labour market shocks are statistically significant, we calculate quantile effects on inter-percentile ranges together with standard errors. These are displayed in Panels 2A-2C, in which we compare the distributional ranges, the widest 10-50-90 and the slightly narrower 25-50-75.<sup>12</sup> In general, all three of the main labour market shocks have very similar magnitudes between them. Thus the 10-90 distance for salary and hours reduction is statistically identical to entry into unemployment and having filed for unemployment benefits. Thus, for *any shocks* in Panel 2C, we note that the difference between the 90<sup>th</sup> percentile and the 10<sup>th</sup> percentile of the financial wellbeing distribution is 15.5 points (and statistically significant). In the lower half of the distribution, the distance between the 10<sup>th</sup> percentile and the median is 5.8 points, although not significant. We compare this to the upper half of the distribution, where this (significant) difference is 9.6 points.

We can compare the 90-10 results to the more conservative 75-25 results, but still find across the board statistically and economically significant differences (albeit slightly narrower) across the financial wellbeing distribution. For *any shocks* in 90-10, there is a 15.5-point difference, whereas for 75-25, this difference is slightly lower at 12.3.

Overall, Panels 2A-2C show that COVID-19 labour market shocks are primarily related to lower financial wellbeing among people in the low end of the financial wellbeing distribution, and that these shocks generally increase inequality in financial wellbeing. In the next section we turn to our counterfactual distribution analyses where we focus solely on the effect of experiencing any COVID-19 labor market shock since our estimates are so similar across panels A-C of Table 1.

<sup>&</sup>lt;sup>12</sup> Full corresponding estimation results are shown in Table A4.

#### 4.2 Counterfactual distributional analysis

We examine distribution effects using distribution regression as in Chernozhukov et al. (2013), with corresponding and corroborative DiNardo et al (1996) decomposition results in Online Appendix B. The top part of Figure 3 (a) displays all of the point estimates for the linear probability models of Equation (1') for the variable of interest "Any COVID-19 Shock". The point estimates are given by the solid black line, surrounded by 95% confidence intervals in green dashed lines. A red dot is placed on the zero line to indicate whether the distribution regression point estimate is significantly different from zero. As indicated in the top part, all coefficients are significantly different from zero over the entire distribution of financial wellbeing. Furthermore, the F-test of jointly testing whether all coefficients are zero is rejected with higher than 99.9% level of confidence ( $\chi^2 = 124.5$  with 20 degrees of freedom). That would be true of the single OLS point estimate (with 95% confidence interval) as well, seen in the lower part of Figure 3 (a) (bold black line). Additionally, we test jointly whether the coefficients are significantly identical to each other. We reject this also with higher than 99.9% level of confidence ( $\chi^2$ =105.9 with 19 degrees of freedom). The top panel of Figure 3 (a) demonstrates that the largest negative distributional association of "Any COVID-19 Shock" with the financial wellbeing distribution is seen between the values of financial wellbeing of 40 and 75.

#### < Figure 3 here >

In Figure 3 (b), for those individuals who experienced a COVID-19  $Shock_{it}$ , we can calculate (1) an observed distribution of financial wellbeing, and (2) a counterfactual distribution of financial wellbeing, in which we remove the association with  $Shock_{it}$  at each discrete value of the  $FWB_{it}$  distribution. We provide the probability density functions (PDFs, bottom part) and the cumulative density functions (CDFs, top part) of the observed and counterfactual distributions.

In the bottom panel of Figure 3 (b), we see the treated PDF as observed (dark bars) and the counterfactual PDF (grey bars). As seen by the grey bars, removing the negative association with the COVID-19 shocks, moves the distribution rightward. In the top panel of Figure 3 (b), the observed CDF starts off much higher at lower values of financial wellbeing, as more of the mass is observed there. Between the FWB values of 40 and 75 the vertical distance between

the treated CDF as observed and the counterfactual CDF is highest, indicating the largest influence in the distribution.

We see this numerically as well in the notes below the bottom panel of Figure 3(b), in which distributional statistics are reported. The median value of 45 in the observed distribution of the treated moves counterfactually to the right to 65, having removed the negative association with COVID-19 shocks. The standard measure of inequality, the 90/10 ratio, goes from 8 (=80/10) to 3.2 (=95/30). Similarly, the Gini inequality coefficient drops from 0.283 to 0.203. If the outcome variable were income, these differences in inequality would be considered to be a very large in the international literature. While any COVID-19 labour market impacts have an overall average negative association of -17.9 points with financial wellbeing, there are substantial and significant distributional associations differing by position in the financial wellbeing distribution.

## 5. Conclusions

In this study, we conducted an online survey *COVID-19 and YOUR Wellbeing* which surveyed internet respondents in 3 months of the beginning of the COVID-19 crisis in Australia (April-July 2020), and which was weight-stratified by age and gender to make it representative of the Australian population. We examine the financial wellbeing effects associated with having experienced (a) a reduction in earnings and hours worked or (b) entry into unemployment or having filed for unemployment benefits. Examining these relationships is important to identify vulnerable populations in the pandemic, necessary for targeting policy interventions, as well as understanding whether current government policies are sufficient to protect those vulnerable to labour market shocks and their potential financial wellbeing implications. Using a validated measure of financial wellbeing, this is the first paper to quantify empirically the association of COVID-19 related labour market shocks with financial wellbeing. Almost 32% of Australians experienced at least one labour market shock. Similarly, a significant proportion of Australians report having troubles with their financial wellbeing.

Having experienced any of the examined COVID-19 related labour market shocks is significantly associated with a 29% reduction in financial wellbeing (or 17.9-points on the 0-100 financial wellbeing scale). We identify large inequalities across the financial wellbeing

distribution. Unconditional quantile effects reveal that the relationship is strongest at the bottom of the distribution: for the 25<sup>th</sup> percentile an experience of any of the shocks is associated with a drop of 28 points, whereas the 75<sup>th</sup> percentile experiences only a 16-point drop. Distribution regressions suggest large potential gains in equality in financial wellbeing if one were to counterfactually remove the negative associations of COVID-19 labour market shocks with financial wellbeing across the distribution. Specifically, we find that the standard measure of inequality, the 90/10 ratio, goes from 8 in the observed distribution of the treated to 3.2 having counterfactually *removed* the negative association with COVID-19 shocks; similarly, the Gini inequality coefficient drops from 0.283 to 0.203. Thus, counterfactual distribution regressions indicate a shifting of the financial wellbeing distribution leftwards brought on by those suffering a COVID-19 labour market shock, indicating potential significant increases in financial wellbeing disadvantage and inequality. These conclusions are consistent with a corresponding DiNardo et al (1996) decomposition outlined.

Our results have important implications for policy. First, we see significant associations of the labour market shocks with financial wellbeing *despite* Australian active labour market programs of "JobSeeker", providing non-means-tested base level support for the unemployed, and "JobKeeper", providing a firm-paid wage subsidy for those still employed at a struggling firm. Second, it is important to note, that those still in the labour market and not yet unemployed, but having experienced a reduction in salary and hours worked, nonetheless experience lower levels of financial wellbeing, about equal in magnitude to those officially having lost their jobs or having applied for unemployed", their financial wellbeing is just as precarious as those explicitly unemployed due to COVID-19 are at least still "employed", that Australians regain much higher levels of *real employment*.

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# **Figures and Tables**



# Figure 1: Financial well-being questions and financial well-being measure

**Note:** The graph shows the underlying subcomponents of financial well-being and the proportion of people who selected each potential answer per subcomponent (the grey bars). The orange line shows how the subcomponents relate to financial well-being: it graphs the average financial well-being score for everyone who selected each of the respective response options.

Figure 2: Distribution of Financial Wellbeing (FWB): Observed and Treated (Any COVID-19 Shock)



Note: The graph compares the observed probability density function (PDF) of financial wellbeing (dark grey bars) to that of the "treated" subpopulation of those who have experienced any COVID-19 shocks (light grey bars), as factually observed. All statistics are population weighted for representativity.



## Figure 3: Distribution Regression: Any COVID19 Shock



(b) Any Shock CDF & PDF over FWB

Note: The top panel of (a) displays the individual distribution regressions (linear probability models or LPM) at every point in the financial wellbeing distribution. The point estimate is given by the dark black line and the respective 95% confidence interval by the surrounding dashed green lines. The summation of these individual effects over the entire distribution gives exactly the overall OLS coefficient, shown in the bottom panel of (a) (bold black line with dashed green line showing the 95% confidence interval). As the association with any COVID-19 related labour market shock (AnyShock) is negative, the negative association is summed up (the curved light black line) over the entire distribution of financial wellbeing and exactly equals the value of the estimated OLS coefficient. In both panels, a red dot is shown on the zero line to indicate an estimated coefficient that is significantly different from zero. The "step function" appearance of the estimated coefficients in the top panel comes from the fact that there are at most 21 distinct values in the 0 through 100 scale (0, 5, 10, 15, ..., 100). The top panel of (b) shows for the group of people experiencing any COVID-19 related labour market shock (AnyShock) the observed cumulative density function (CDF) over the distribution of financial wellbeing (solid blue line). Using the coefficients of the distribution regression estimations, the association of AnyShock with financial wellbeing is removed, producing the counterfactual CDF shown in dashed red. The bottom panel displays the corresponding probability functions (PDF) as histograms. The dark bars display the values of financial wellbeing as observed for those experiencing AnyShock. The counterfactual histogram in lighter grey removes the association of AnyShock with financial wellbeing. Online Appendix B shows the corresponding DiNardo, Fortin and Lemieux (1996) decomposition approach to financial wellbeing, which essentially treats financial wellbeing as a continuous variable as it uses kernel density estimations.

Variable	(1) Maan	(2)	(3)	(4)	(5) 075	(6) 090
	Ivitan	QIU	Q25	Q30	Q/5	Q90
171. Solory & Hours	18 871***	24 621***	30 730***	10 000***	1/1 336***	7
Salary & Hours	(1.015)	-24.021	(3.770)	(1.986)	(2.052)	(1.776)
[Bounds: R. R.]	[_18 821	(+.+)3)	(3.770)	(1.900)	(2.052)	(1.770)
[Dounds: $p_0, p_1$ ]	-15 901					
$\delta$ rea'd for $\beta = 0$	2 77	_	_	_	_	_
$\frac{1}{18}$	2.17					
LIE or Benefits	-15 808***	-21 463***	-21 794***	-14 775***	-15 119***	-8 879***
OL OF Denemos	(1.915)	(4 458)	$(4\ 040)$	(2 363)	(2.080)	(1.550)
[Bounds: $\beta_0$ , $\beta_1$ ]	[-15.808.	(1.150) -	(1.010)	(2.303)	(2.000)	(1.550)
[Dounds: p(),p1]	-10.2]					
$\delta$ reg'd for $\beta = 0$	1.84	_	-	-	-	-
1C.						
Any Shocks	-17.860***	-23.322***	-27.837***	-17.490***	-15.547***	-7.868***
J	(1.876)	(4.179)	(3.696)	(2.102)	(2.086)	(1.752)
[Bounds: $\beta_0, \beta_1$ ]	[-17.860,	-	-	-	-	-
	-12.8]					
$\delta$ req'd for $\beta = 0$	1.93	-	-	-	-	-
- ·						
	I(90-10)	I(50-10)	I(90-50)	I(75-25)	I(50-25)	I(75-50)
2A.						
Salary & Hours	17.394***	4.721	12.673***	16.403***	10.840***	5.563**
-	(4.659)	(4.289)	(2.015)	(3.588)	(2.968)	(1.771)
2B.						
UE or Benefits	12.634**	6.688	5.946*	6.676	7.019*	-0.343
	(4.573)	(4.257)	(2.390)	(3.964)	(3.071)	(2.288)
2C.						
Any Shocks	15.454***	5.833	9.621***	12.290***	10.348***	1.943
	(4.362)	(3.993)	(2.147)	(3.524)	(2.813)	(1.918)
Demographic	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$
controls						
Labour market status:						
Not working	$\checkmark$	✓	<b>√</b>	<b>√</b>	<b>√</b>	<b>√</b>
Occupation FE	<b>√</b>	✓	<b>√</b>	<b>√</b>	<b>√</b>	<b>√</b>
State FE	<b>√</b>	✓	<b>√</b>	<b>√</b>	<b>√</b>	<b>√</b>
Week Time Trend	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$

**Table 1: Covid-19 Labour Market Shocks and Financial Wellbeing** 

Note: \* p < 0.1, \*\* p < 0.05, \*\*\* p < 0.01. Standard errors in parentheses. Each panel 1A- 1C is from a separate regression with financial wellbeing as the dependent variable and each of the COVID-19 labour market impact variables as the regressor of interest respectively. N = 2,325.  $R^2$  ranges from 0.207 to 0.236 in the OLS regression for the effects at the mean. The reported bounds show the sensitivity of the COVID-19 labour market shock estimates to selection on unobservables based on selection on observables. The bounds analysis assumes  $R_{max}$  = 1.3(R<sup>2</sup>), where R<sup>2</sup> is from the OLS regressions with all controls. The lower bound  $\beta_0$  is calculated on the basis that the proportional degree of selection on unobservables to selection on observables is 0 ( $\delta$ =0) and is therefore equivalent to our estimate for  $\beta$ , while the upper bound  $\beta_1$  is calculated on the basis that the amount of selection on unobservables is equal to selection on observables ( $\delta$ =1). The estimated  $\delta$  suggests that there must be  $\delta$  times the amount of selection on unobservables, relative to selection on observables, for the estimated effect to become insignificant. Demographic controls: age, gender, household size. Occupation fixed effects: Managers, Professionals, Trades workers, Personal service, Clerical, Sales, Machinery operators, Labourers, Other. Panels 2A- 2C show the inter-percentile ranges at two points in the financial wellbeing distribution, e.g. the difference in financial wellbeing at the 90<sup>th</sup> percentile compared to that at the 10<sup>th</sup> percentile in column (1) labelled I(90-10). The larger this number, the more dispersion is observed. All dispersion measures here are presented with their respective standard errors to indicate significance of the inter-percentile difference. These results follow from the regressions from the results in Panels 1A-1C. R<sup>2</sup> ranges from 0.119 for I(90-10) to 0.031 for I(75-50).

# **Online Appendix A**





(a) Employed persons ('000)





(b) Unemployed persons ('000)



Underutilisation rate in %





## (e) Monthly hours worked in all jobs ('000)

# (f) Google search for *Centrelink*

Note: for (a)-(e) Data from ABS Labour Force Australia Cat. No. 6202.0. and (f) from Google Trends

# Underutilisation in %

# **Figure A2: Unconditional Quantile Regression: Coefficients over Financial Wellbeing Distribution**



**Note:** The top panel shows the estimated regression coefficients (Table 1, Panel 2C) of the *unconditional* quantile regression at various percentiles (10, 25, 50, 75 and 90) of the financial wellbeing distribution (black line). The point estimates are bounded in a 95% confidence interval (green dashed lines). For the unconditional quantile estimate to be relevant, there needs to be sufficient variation in the estimated coefficients over the distribution. Traditionally one calculates inter-percentile ranges and tests for the significance of differences between the percentiles 90-10 or 75-25. The bottom panel shows the average OLS coefficient (-17.9) which does not change over the distribution of financial wellbeing (black line). The quantile coefficient at the 25<sup>th</sup> percentile (-27.8) is larger in absolute terms than the OLS estimate (-17.9) and at the 90<sup>th</sup> percentile (-7.9), the estimated coefficient is much lower. The red dots on the zero line in both graphs indicate an estimated coefficient that is significantly different from zero.

	Obs	Mean	S.D.	Min	Max
Financial wellbeing	2,325	61.5167	25.4169	0	100
Reduced salary with reduced hours	2,325	0.2574	0.4373	0	1
Unemployment or benefits	2,325	0.2221	0.4157	0	1
Any impact	2,325	0.3183	0.4659	0	1
Week of year	2,325	20.8441	3.4089	16	27
Household size	2,325	2.9083	1.3485	1	6
Male	2,325	0.4950	0.5001	0	1
Grouped age	2,325	4.1309	1.2683	2	6
- 18-24	148	0.1062	0.3082	0	1
- 25-34	333	0.2439	0.4295	0	1
- 35-44	558	0.2472	0.4315	0	1
- 45-54	691	0.2182	0.4131	0	1
- 55-64	595	0.1845	0.3880	0	1
Occupation	2,325	34.0332	28.9113	0	98
- Not employed	204	0.0797	0.2709	0	1
- Managers	239	0.1154	0.3196	0	1
- Professionals	878	0.4211	0.4938	0	1
- Trades workers	73	0.0578	0.2335	0	1
- Personal service	192	0.0569	0.2317	0	1
- Clerical	266	0.0686	0.2528	0	1
- Sales	100	0.0480	0.2139	0	1
- Machinery ops	25	0.0180	0.1329	0	1
- Labourers	30	0.0164	0.1272	0	1
- Other	318	0.1180	0.3227	0	1
	2,325	5.3180	2.2196	1	8
State	50	0.0235	0.1514	0	1
- ACT					
- NSW	474	0.2116	0.4085	0	1
- NT	18	0.0066	0.0810	0	1
- QLD	302	0.1282	0.3344	0	1
- SA	144	0.0593	0.2363	0	1
- TAS	90	0.0375	0.1900	0	1
- VIC	1,076	0.4492	0.4975	0	1
- WA	171	0.0841	0.2775	0	1

**Table A1: Weighted descriptive statistics** 

	Size	Salary red	Salary reduction		oyment	Any sł	nock
	%	Mean	Std.	Mean	Std.	Mean	Std.
Household size							
1	13.56%	0.24	0.43	0.18	0.39	0.30	0.46
2	33.66%	0.25	0.44	0.22	0.42	0.30	0.46
3	18.66%	0.23	0.42	0.23	0.42	0.31	0.46
4	20.72%	0.25	0.43	0.22	0.41	0.32	0.47
5	9.33%	0.35	0.48	0.25	0.43	0.40	0.49
6+	4.07%	0.30	0.46	0.24	0.43	0.38	0.49
Gender							
Female	50.50%	0.30	0.46	0.26	0.44	0.37	0.48
Male	49.50%	0.21	0.41	0.18	0.38	0.26	0.44
Age							
18-24	10.62%	0.30	0.46	0.37	0.48	0.44	0.50
25-34	24.39%	0.20	0.40	0.15	0.36	0.24	0.43
35-44	24.72%	0.27	0.45	0.24	0.43	0.35	0.48
45-54	21.82%	0.24	0.43	0.20	0.40	0.27	0.45
55-64	18.45%	0.32	0.47	0.23	0.42	0.36	0.48
Employment stat	us + Occup	ation					
Not employed	7.97%	0.42	0.50	0.64	0.48	0.67	0.47
Managers	11.54%	0.20	0.40	0.15	0.36	0.23	0.42
Professionals	42.11%	0.15	0.35	0.09	0.29	0.18	0.38
Trades							
Workers	5.78%	0.29	0.46	0.20	0.41	0.30	0.46
Service	5.69%	0.30	0.46	0.22	0.41	0.35	0.48
Clerical	6.86%	0.24	0.43	0.18	0.38	0.29	0.45
Sales	4.80%	0.35	0.48	0.46	0.50	0.60	0.49
Machinery Ops	1.80%	0.36	0.49	0.28	0.46	0.41	0.50
Labourers	1.64%	0.71	0.46	0.64	0.49	0.71	0.46
Other	11.80%	0.45	0.50	0.35	0.48	0.50	0.50

# Table A2: Descriptive statistics of COVID-19 shocks by covariates

**Note:** N = 2,325. Statistics are population weighted based on age and gender.

	(1)	(2)	(3)	(4)	(5)	(6)
Week of Veer	0.208	Q(10)	Q(25)	Q(50)	Q(75)	Q(90)
week of fear	(0.298)	(0.394)	(0.390)	(0.320)	(0.344)	-0.181
Household size	0.057	(0.394)	0.590)	(0.329)	0.266	-0.997
Household size	(0.644)	(1.258)	(1.268)	(0.785)	(0.200)	(0.784)
Male	3 345	2 869	2 548	1 869	4 757	3 493
Male	(1.801)	(3 383)	(3.270)	(2.412)	(2.646)	(2, 321)
Age Group:	(1.001)	(5.565)	(3.270)	(2.112)	(2.010)	(2.321)
18-24	-4.853	-10 947	-11 010	-2.994	-2.278	-1.955
10 21	(3.198)	(7.077)	(6.506)	(4.096)	(4.910)	(4.042)
25-34	-0.562	-0.634	0.445	1.113	-2.548	-1.495
	(1.486)	(2.423)	(2.517)	(1.947)	(2.486)	(2.229)
35-44	-0.371	4.006	-0.156	-1.510	-0.060	-0.204
	(1.297)	(2.220)	(2.440)	(1.713)	(2.041)	(1.764)
45-54	0.936	-1.696	1.462	0.931	0.399	-1.006
	(1.209)	(2.313)	(2.027)	(1.558)	(2.066)	(1.814)
55-64	2.927	3.779	4.229	1.174	4.287	4.564*
	(1.528)	(2.687)	(2.672)	(1.818)	(2.244)	(2.157)
Occupation:						
Not employed	-14.166***	-13.882**	-26.546***	-11.656***	-10.860***	-7.910***
	(2.502)	(5.226)	(5.508)	(2.964)	(2.775)	(1.242)
Managers	5.390**	$7.448^{***}$	6.046	$5.278^{*}$	5.560	7.789
	(2.084)	(2.134)	(3.162)	(2.390)	(3.710)	(4.237)
Professionals	3.711***	2.519	5.937***	3.869**	$4.811^{**}$	0.582
	(0.933)	(1.615)	(1.691)	(1.220)	(1.485)	(1.301)
Trades Workers	-1.039	-3.803	2.707	-2.880	-1.351	8.741
	(4.183)	(5.564)	(6.425)	(5.239)	(5.990)	(6.483)
Personal Service	-3.062	-8.365	-5.373	-4.753	-1.087	2.527
	(4.054)	(10.393)	(6.390)	(3.795)	(4.775)	(4.948)
Clerical	-2.432	7.064**	0.617	-1.589	-7.378**	-7.658***
	(1.429)	(2.308)	(3.124)	(2.375)	(2.727)	(1.435)
Sales	-2.472	0.314	-2.303	-4.286	-9.089	-3.361
	(3.447)	(8.356)	(7.943)	(5.602)	(3.610)	(3.021)
Machinery Ops	-4.86/	-12.8/6	6.808	3./10	-6.325	-10.688
T 1	(7.114)	(16.631)	(10.743)	(7.907)	(8.289)	(5.612)
Labourers	-2./19	22.959	-14.953	-3.6//	-16.1/3	-1.323
Other	(3.759)	(7.462)	(13./11)	(7.008)	(4.500)	(2.728)
Other	-5.410	-0.407	-0.273	-4.770	-2.001	-1.567
State	(1.707)	(3.000)	(5.344)	(2.322)	(2.339)	(2.232)
	2 524	6 788	0.830	0.258**	7 760	10 244
ACT	(4.152)	-0.788	(5.021)	(3,506)	(9.320)	(10.244)
NSW	-0.577	2 885	-3 627	-3 113	-0.106	-1 879
100	(1.387)	(2,237)	(2.812)	(1.994)	(2 421)	(1.949)
NT	5 093	10 113	2.867	4 183	9 286	10 740
	(13.012)	(7, 287)	(13, 897)	(14.063)	(19.292)	(18 965)
OLD	0.535	0.339	-1.826	0.829	1.594	3.120
<b>X</b>	(2.105)	(2.722)	(3.352)	(2.381)	(3.504)	(3.625)
SA	-2.711	-13.443	-9.483	-1.549	0.496	0.281
	(4.600)	(10.891)	(8.400)	(4.672)	(4.870)	(4.426)
TAS	-4.793	-24.747**	-5.345	-0.474	4.826	4.083
	(3.586)	(8.631)	(6.196)	(3.802)	(4.580)	(4.350)
VIC	0.644	1.997	3.478	0.956	-1.546	-0.517
	(0.804)	(1.360)	(1.383)	(1.048)	(1.328)	(1.211)
WA	0.142	3.177	1.950	-0.147	0.695	-2.987
	(2.406)	(3.054)	(3.799)	(3.513)	(5.008)	(3.509)
Any Impact	-17.860***	-23.322***	-27.837***	-17.490***	-15.547***	-7.868***
	(1.876)	(4.179)	(3.696)	(2.102)	(2.086)	(1.752)
Constant	59.173***	$27.014^{*}$	35.270***	67.422***	76.934***	104.823***
	(5.531)	(10.622)	(10.173)	(7.822)	(7.699)	(6.072)
Adj. R <sup>2</sup>	.212	.119	.175	.135	.0915	.0615
N	2325	2325	2325	2325	2325	2325
Bound	-12.8					
Delta	1.93					

# Table A3: Financial Wellbeing: Any COVID-19 shocks

Note: N=2325. \* p < 0.05, \*\* p < 0.01, \*\*\* p < 0.0. Dummy variable sets for occupation, state and age are reported as deviations from their respective weighted averages as in Haisken-DeNew and Schmidt (1997), and not in relation to an arbitrary reference category.

	(1)	(2)	(3)	(4)	(5)	(6)
	I(90-10)	I(50-10)	I(90-50)	I(75-25)	I(50-25)	I(75-50)
Week of Year	-0.538	-0.132	-0.406	-0.427	-0.546	0.119
	(0.460)	(0.425)	(0.358)	(0.474)	(0.347)	(0.345)
Household size	-0.799	0.142	-0.941	-0.411	-0.733	0.322
	(1.442)	(1.300)	(0.900)	(1.261)	(0.962)	(0.773)
Male	0.624	-1.000	1.624	2.209	-0.679	2.888
	(3.883)	(3.365)	(2.798)	(3.604)	(2.580)	(2.545)
Age Group:						
18-24	8.992	7.953	1.039	8.732	8.016	0.716
	(7.608)	(6.745)	(4.636)	(6.354)	(4.778)	(4.078)
25-34	-0.861	1.746	-2.608	-2.993	0.668	-3.661
	(3.199)	(2.773)	(2.482)	(3.142)	(2.256)	(2.310)
35-44	-4.209	-5.516*	1.306	0.095	-1.354	1.450
	(2.767)	(2.514)	(2.014)	(2.777)	(2.134)	(1.802)
45-54	0.690	2.627	-1.937	-1.063	-0.531	-0.532
	(2.825)	(2.404)	(2.034)	(2.485)	(1.796)	(1.790)
55-64	0.785	-2.605	3.390	0.059	-3.055	3.113
	(3.263)	(2.720)	(2.209)	(2.790)	(2.102)	(1.784)
Occupation:	· · · ·	× /	· · · ·			<b>`</b>
Not employed	5.972	2.226	3.746	15.686**	$14.890^{***}$	0.796
- · · · · · · · · · · · · · · · · · · ·	(5.351)	(5.176)	(2.928)	(4.852)	(3.610)	(2.660)
Managers	0.341	-2.170	2.511	-0.486	-0.768	0.282
1. Tuning et s	(4.551)	(3.016)	(3.893)	(4.111)	(2.896)	(3.128)
Professionals	-1.937	1.350	-3.287*	-1.126	-2.068	0.942
11010001011410	(2.010)	(1.787)	(1.467)	(1914)	(1.446)	(1.320)
Trades Workers	12.543	0.922	11 621*	-4 058	-5 587	1 529
fiddes wonders	(8.039)	(7.097)	(5.902)	(7 586)	$(6\ 160)$	(5,357)
Personal Service	10 892	3 612	7 280	4 287	0.620	3 667
i ersonar bervice	(9.914)	(8 219)	(4 101)	(5.061)	(4 146)	(2.917)
Clerical	-14 722***	-8 653**	-6.069*	-7 995*	-2 206	-5 789
Cleffedi	(2, 600)	(3.113)	(2.811)	(3 738)	(2.557)	(2.986)
Sales	-3 676	-4 600	0.924	-6 786	-1 983	-4 803
Sales	(8.674)	(8 103)	(5.678)	(8 294)	(6.042)	(5,546)
Machinery Ons	2 189	(6.105)	(3.078)	(0.294)	(0.042)	(3.340)
Machinery Ops	(16,700)	(13,600)	(8352)	$(11\ 167)$	-3.098	(7,005)
Labourara	(10.709)	(13.000) 26.627*	(0.552)	(11.107)	(0.372)	(7.903)
Labourers	-30.283	(10.428)	-3.040	(16.075)	(8.526)	(0.826)
Other	(7.470)	(10.428)	(0.419)	(10.073)	(8.520)	(9.850)
Oulei	(4.224)	(2.807)	3.369	(2.085)	(2.281)	(2, 370)
State	(4.234)	(3.897)	(2.034)	(3.983)	(5.281)	(2.570)
	17.022	16 046***	0.087	6.020	8 410**	1 100
ACI	(11.249)	(4, 700)	(10,592)	(0.930)	(2, 151)	-1.400
NCM	(11.546)	(4.790)	(10.385)	(9.081)	(5.151)	(9.184)
INDIV	-4.704	-3.998	(2, 202)	(2.120)	(2.471)	(1.051)
NT	(2.923)	(2.810)	(2.293)	(3.129)	(2.471)	(1.931)
IN I	(14.457)	-5.930	0.330	0.420	1.31/	5.105
	(14.457)	(9.969)	(10.064)	(11.859)	(9.171)	(7.876)
QLD	2.780	0.490	2.290	3.420	2.655	0.765
<b>C</b> A	(4.303)	(3.248)	(3.396)	(3.939)	(2.706)	(2.999)
SA	13.723	11.894	1.829	9.979	/.935	2.045
<b>m</b> + 0	(10.327)	(9.012)	(4.499)	(6.518)	(4.800)	(3.586)
TAS	28.830**	24.273**	4.557	10.171	4.871	5.300
	(9.409)	(7.609)	(4.949)	(7.317)	(4.954)	(4.341)
VIC	-2.515	-1.041	-1.473	-5.024**	-2.522*	-2.502*
	(1.775)	(1.512)	(1.338)	(1.687)	(1.228)	(1.225)
WA	-6.164	-3.324	-2.840	-1.255	-2.098	0.843
	(4.725)	(4.066)	(4.330)	(5.136)	(3.716)	(3.952)
Any Impact	15.454***	5.833	9.621***	12.290***	10.348***	1.943
	(4.362)	(3.993)	(2.147)	(3.524)	(2.813)	(1.918)
Constant	77.810***	$40.409^{***}$	37.401***	41.664***	32.153***	9.511
	(11.925)	(10.796)	(8.475)	(11.477)	(8.246)	(8.189)
Adj. R <sup>2</sup>	0.0574	0.0329	0.0410	0.0438	0.0529	0.0143

Table A4: Financial Wellbeing: Any COVID-19 shocks Inter-percentile Range

Note: N=2325. \* p < 0.05, \*\* p < 0.01, \*\*\* p < 0.001. Dummy variable sets for occupation, state and age are reported as deviations from their respective weighted averages as in Haisken-DeNew and Schmidt (1997), and not in relation to an arbitrary reference category.

#### Online Appendix B: Additional DiNardo, Fortin and Lemieux (1996, DFL) Analyses

In addition to the distribution regressions (Chernozhukov et al. 2013, 2020a; Chernozhukov et al. 2020b; and Van Kerm 2015), we also apply the well-known DiNardo, Fortin and Lemieux (1996) decomposition approach to financial wellbeing, which treats financial wellbeing as a continuous variable. This will allow us to calculate a counterfactual financial wellbeing distribution for those "treated" with  $Shock_{it}$ , yet net of the COVID-19 shock. Given that the vector of characteristics for those having experienced the COVID-19  $Shock_{it}$  is likely to be systematically different from those who did not, we must control explicitly for this.

The DiNardo et al. (1996) decomposition consists of estimating the following set of equations:

$Prob(Shock_{it}) = \Phi(Demog_{it}\beta + \varepsilon_{it})$		(1a)
$DFL_w = (1 - \widehat{Shock_{\iota t}}) / \widehat{Shock_{\iota t}}$	if $Shock_{it} = 1$	(1b)
$kdensity FWB_{it} [weight = 1]$	if $Shock_{it} = 1$	(1c)
$kdensity FWB_{it} [weight = DFL_w]$	if $Shock_{it} = 1$	(1d)

In the first step we estimate a non-linear binary probit probability model of  $Shock_{it}$ , where *Prob* denotes the probability and  $\Phi$  is the cumulative distribution function of the standard normal distribution, using the demographic controls as explanatory variables as in (1a) to construct the DiNardo et al. (1996) counterfactual weight  $DFL_w$  in (1b). We compare the factual density of  $FWB_{it}$  with  $Shock_{it} = 1$  in (1c) with the *counterfactual* density of  $FWB_{it}$  with  $Shock_{it} = 1$  weighted by  $DFL_w$  in (1d), i.e. weighted to have the characteristics of those not experiencing the  $Shock_{it}$ . The difference is the distributional (counterfactual) association of  $Shock_{it}$  with the factual distribution of  $FWB_{it}$ . We are interested in the counterfactual shifts of the  $FWB_{it}$  distribution associated with  $Shock_{it}$ .

Having created the factual and counterfactual probability density functions (PDF), we integrate over them to recreate the cumulative distribution function  $\Phi$  (CDF) and calculate measures of inequality/dispersion to assess the extent to which financial wellbeing inequality is associated with *Shock<sub>it</sub>*. For the factual and counterfactual distributions, we calculate the mean, the standard deviation of financial wellbeing, and the head-count ratio of 50% of the median, similar to the standard measure found in the income inequality literature. Further, we focus on calculating the *FWB<sub>it</sub>* distance between the 25, 50 and 75-percentiles of the distribution: specifically, 75-25, 75-50, and 50-25. This allows us to have an overall measure of dispersion (75-25) and investigate how this might be changing depending on having experienced one of the COVID-19 labour market shocks  $Shock_{it}$ , as well as measures specific to the left (50-25) and right (75-50) tail of the  $FWB_{it}$  distribution.

We present the results in Table B1 with first step results in Table B2. In Panel A of Table B1, following DiNardo et al. (1996), we calculate the values of financial wellbeing at different points in the observed distribution. In the first row in Panel B, we do the same for those experiencing any labour market shocks due to COVID-19. In the second row of Panel B, we take those individuals as in the first row of Panel B, but weight them counterfactually with the characteristics as if they had not had these shocks. Row three of Panel B shows the same results for those fortunate to not have suffered any COVID-19 shocks. The right three most columns are measures of inequality: taking the value of financial wellbeing at the 75th percentile minus that of the 25th percentile (inequality over most of the distribution), the 75th percentile minus that of the 50th percentile (right tail inequality) and finally the 50th percentile minus that of the 25th (left tail inequality). Thus, for those treated with any shocks, inequality in financial wellbeing using the inter-percentile range 75-25 difference increases from 36.1 without having experienced any shocks to 38.3 when having indeed experienced any shocks. Moreover, much of the mass of density of financial wellbeing for those having experienced shocks shifts leftward.

Figure B1 shows graphically that the COVID-19 labour market shocks are associated with a general worsening of financial wellbeing distribution and an increase in inequality of financial wellbeing. The head-count-ratio (HCR), i.e. the share of the distribution that is situated to the left of the vertical line at 32.5 (on the 0 to 100 FWB scale) is 24.6% <sup>13</sup> for those counterfactually not having experienced any COVID-19 labour market shocks. This increases to 28.4% for those experiencing any labour market shock. This head-count-ratio is analogous to the poverty rate, or poverty head-count-ratio, in the earnings inequality literature, such as the FGT(0) measure of Foster, Greer and Thorbecke (1984, 2010).

 $<sup>^{\</sup>rm 13}$  50% of the median FWB value of 65 is 32.5.



Figure B1: Financial Wellbeing (FWB) decomposition by Any COVID-19 shocks

**Note:** DiNardo et al. (1996) decomposition of financial wellbeing (FWB) by whether individuals have experienced any shock (AnyShock). Top left figure displays the factual densities of FWB population/sample weighted (thick black line), factual FWB density for those (AnyShock=1, red) and factual FWB density for those (AnyShock=0, green). Top right figure displays observed distribution of FWB for those having experienced AnyShock (solid red line) compared to the counterfactual distribution of FWB (dash red line) weighted *not* to have experienced AnyShock (CF:AnyShock=0). Bottom right figure displays the difference in density (blue line) of the two top right densities: (AnyShock=1) minus (CF:AnyShock=0). Bottom left figure displays the observed distribution of FWB (dash red line) weighted *not* to have experienced AnyShock (CF:AnyShock=1) minus (CF:AnyShock=0). Bottom left figure displays the observed distribution of FWB (dash red line) weighted *not* to have experienced AnyShock (CF:AnyShock=1) minus (CF:AnyShock=0). Bottom left figure displays the observed distribution of FWB (dash red line) weighted *not* to have experienced AnyShock (CF:AnyShock=0). Left of the vertical dotted black line at 32.5 on the FWB 0 to 100 scale, or 50% of median value (65.0) of the FWB distribution, refers to the most vulnerable in terms of FWB. Any increase in density to the left of the vertical dotted line indicates an increase in prevalence of extremely low levels of FWB.

	Mean	FWB	HCR	Per	centiles F	WB	Inter-p	ercentile I	Range
Distribution	Mean	Std.	50% (Med)	25%	50%	75%	75%- 25%	75%- 50%	50%- 25%
<b>A.</b>									
FWB: As observed	56.465	23.406	0.143	44.541	64.941	81.688	37.147	16.746	20.400
В.									
FWB   Any Shock	44.589	23.418	0.284	29.883	48.630	68.160	38.278	19.530	18.747
FWB: CF No Shock	47.847	22.579	0.246	32.884	52.545	68.987	36.103	16.442	19.661
FWB   No Shock	62.066	20.851	0.076	55.111	70.335	86.298	31.187	15.963	15.224

Table B1: DiNardo et al. (1996) FWB Decompositions by COVID-19 Shocks

**Note:** CF = Counterfactual, FWB = financial wellbeing, HCR = Head-Count-Ratio (50% of median FWB value of 65) at 32.5 on 0 to 100 FWB scale.

Variable	0	Manginal Effect
variable	β	Marginal Effect
Week of Year	0.025**	0 008**
week of Tear	(0,000)	(0.003)
Household size	(0.009)	0.000
Household size	(0.029	(0.009
	(0.022)	(0.007)
Male	-0.209	-0.064
	(0.065)	(0.020)
Age Group:		
18-24		
25.24	0.051*	0.075*
25-34	-0.251	-0.075
	(0.112)	(0.035)
35-44	0.116	0.038
	(0.110)	(0.035)
45-54	-0.183	-0.056
	(0.113)	(0.035)
55-64	0.077	0.025
	(0.116)	(0.037)
Occupation:		
Not employed		
Managers	-1.121***	-0.406***
8	(0.131)	(0.044)
Professionals	-1.276***	-0.449***
	(0.108)	(0.038)
Trades Workers	-0.821***	-0.308***
fiddes workers	(0.155)	(0.055)
Personal Service	-0.843***	-0.316***
reisonal Service	-0.843	-0.310
Clarical	(0.149)	(0.033)
Ciencal	-1.050	-0.378
S - 1	(0.146)	(0.049)
Sales	-0.220	-0.082
	(0.161)	(0.060)
Machinery Ops	-0.554	-0.210
	(0.222)	(0.084)
Labourers	0.154	0.054
	(0.242)	(0.083)
Other	-0.441***	-0.167***
	(0.124)	(0.046)
State:		
ACT		
NSW	$0.628^{*}$	0.167**
	(0.260)	(0.057)
NT	0.783	0.217
	(0.428)	(0.127)
QLD	0.535*	$0.139^{*}$
	(0.266)	(0.059)
SA	$0.588^{*}$	$0.155^{*}$
	(0.279)	(0.065)
TAS	0.653*	0.175*
	(0.292)	(0.071)
VIC	0.636*	0.170**
	(0.256)	(0.055)
WA	0 378	0.093
	(0.274)	(0.061)
Constant	-0 660	(0.001)
Constant	(0.355)	
	((7).).)	

# Table B2: Financial Wellbeing: DFL Decomposition: 1st Stage

**Note:** N=2325. Probit non-linear regression. \* p < 0.1, \*\* p < 0.05, \*\*\* p < 0.01. Standard errors in parentheses. Reference categories: Female, Age 18-24, not in employment.