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COVID-19 LABOUR MARKET SHOCKS AND THEIR INEQUALITY IMPLICATIONS FOR FINANCIAL WELLBEING

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NON-TECHNICAL SUMMARY

The COVID-19 pandemic has spawned an unprecedented international health and economic crisis. Although some aspects of the macroeconomic consequences have been considered, we know much less about the extent to which the crisis has affected individuals' financial wellbeing or how people are coping financially. Using an online survey of Australian residents, we investigate how labour market shocks (such as experiencing salary and working hour reductions, or becoming unemployed or having to apply for unemployment benefits), as a direct results of COVID-19, are associated with Australians' financial wellbeing. We focus specifically on financial wellbeing rather than income. 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 or constraints. Financial wellbeing as a validated multi-item measure captures 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. Experiencing a reduction in working hours and earnings, entering into unemployment or having to file for unemployment benefits during the pandemic are strongly associated with decrease in financial wellbeing of roughly 29%, despite various government interventions to reduce such effects. We also find that the negative COVID-19 labour market effects are felt most by people who already have low financial wellbeing. Furthermore, the findings suggest potential dramatic increases in financial wellbeing disadvantage and inequality.

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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 around 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 distributional analyses and distribution regression indicate a shifting of the financial wellbeing distribution leftwards brought on by those suffering any of the above-mentioned labour market shocks, indicating potential dramatic increases in financial wellbeing disadvantage and inequality.

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

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1. Introduction

The COVID-19 pandemic has spawned an unprecedented international health and economic crisis. Millions of people have been infected, and hundreds of thousands have died. 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). Botha and de New (2020) examine the association of COVID-19 related underemployment, unemployment and infections with subjective wellbeing in the form of overall life satisfaction and a host of domain satisfactions, including satisfaction with finances. 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).

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.

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 across the financial wellbeing distribution. We analyse the association of financial wellbeing in Australia with experiencing (a) a reduction in earnings and hours worked, (b) entry into unemployment or having filed for unemployment benefits, and (c) having experienced either shock. We use linear regression analysis to assess experiencing COVID-19 shocks on average, unconditional quantile regression to assess experiencing COVID-19 shocks over the entire distribution as well as DiNardo et al. (1996) counterfactual distribution techniques and the results from distribution regressions to calculate counterfactual distributions, net of the COVID-19 shocks. These labour market shocks are associated with shifting the financial wellbeing distribution of those individuals who experienced a COVID-19 labour market shock leftward and increasing dispersion, thereby increasing inequality in financial wellbeing. This is the first paper to demonstrate this relationship with financial wellbeing.

2. Background

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. Since March 17, all international travel is banned by the Australian Government, severely impacting the flight industry. On March 18, social gatherings of more than 100 people indoors were prohibited, affecting large venues and events. A few days later, on March 21, restrictions were put in place to only allow Australian residents to enter Australia, and as such severely impeding the tourism industry as well as the tertiary education sector which heavily depends on international students. 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. It also marked the beginning of the closure of schools in some states. The government struggled to keep up with the demand for welfare payments that started on this day. One could observe long lines of people in front of *Centrelink*, the Australian government's agency responsible for welfare payments. The demand was so high, that the *Centrelink* website crashed. In the following days, starting March 26 further businesses had to close: restaurants, cafes, food courts, and open house inspections. Weddings were restricted to 5 people and funerals to 10.

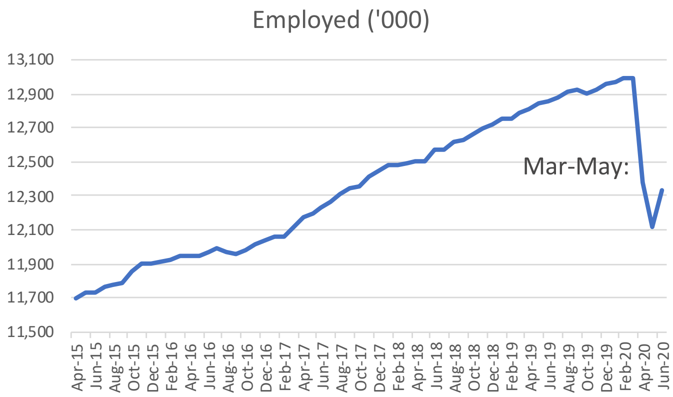
From March 27, many shops began to close and stand down staff. The government urged people to stay at home, other than for essential travel, such as to work or medical appointments. Restrictions were put in place to allow no more than 2 people together in public. After May 15, restrictions on public gatherings slowly started being eased to varying degrees by the state governments, and restaurants and cafes started to transition to open under strict social distancing restrictions. However, this new freedom was cut short by the second wave of COVID-19 infections starting at the end of June. The second wave affected mainly the state of Victoria, with the vast majority of new cases originating there. 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 that could not be done at home, and caregiving.

The various impacts on Australian businesses are reflected in the official labour market statistics in Figure 1. The unemployment rate increased by 2.2%-points from 5.2% in March to 7.4% in June, an increase of 43% (Figure 1 (c)). However, the unemployment rate obscures the full picture, as many people left the labour force altogether, likely too discouraged to look for work in the current economic environment. This can be seen by Figures 1 (a) and (b): While the number of unemployed people increased by 206,847 (+29%) between March and May and by 276,150 (+39%) between March and June, the number of employed people fell by a much larger 871,541 (-7%) and 660,711 (-5%), respectively. Further, the government introduced a wage subsidy (*JobKeeper*), which kept people officially in employment albeit with significant reductions in wages and hours worked. In our analyses, we therefore also look at several labour market statistics that give us a fuller picture: for example, a large number of officially employed people would prefer to work more hours than are currently available to them. If we group these underemployed individuals together with the unemployed, this underutilisation rate is much higher and has larger increases than the unemployment rate, from 14.0% in March to 20.2% in May, an increase of 44% (Figure 1 (d)). It slightly reduced to 19.1% in June when social distancing measured were eased. In a similar manner, the number of monthly hours worked in all jobs captures variation in employment not reflected in the unemployment rate. Between March and May total hours worked decreased by 10% (Figure 1 (e)), with a slight bounce back in hours worked between May and June. In addition to these official labour force statistics, we also show in Figure 1 (f) the Google search frequency (with April 2020 set to 100) for *Centrelink*, where individuals can apply for welfare payments. This should proxy for the general demand for welfare benefit payments. We see a very strong increase of 213% between February and March.

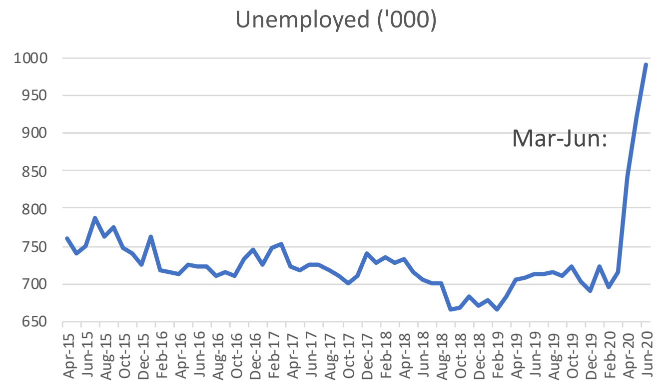
Overall, the statistics point to a significant impact of various labour market shocks on individuals, be it in terms of being made redundant altogether, decreases in wages and/or work hours as well as having to apply for benefits as a consequence of these impacts. The labour market consequences of the pandemic have been more severe for women than men, as women are disproportionally employed in customer-oriented industries, such as retail trade, accommodation and food services, which were more disrupted by social-distancing measures and travel restrictions than other industries.[1] Women's employment fell by 5.6% from March to June compared to only 4.6% for men (ABS Labour Force Australia Cat no. 6202.0).

[1] Under normal economic circumstances, 12% of the female workforce is employed in retail trade and 8% in accommodation and food services. Other industry shares of the total female workforce: Health care and social assistance (23%), education and training (13%), professional scientific and technical services (8%). In comparison, the top industries providing jobs for males are construction (15%), professional, scientific and

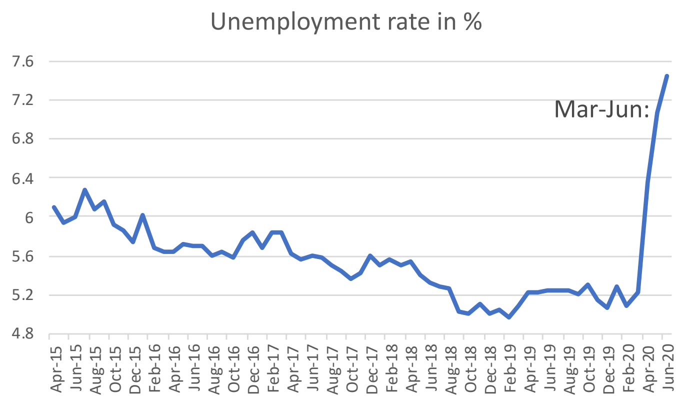
Figure 1: Development of employment, unemployment, underemployment and online welfare searches in Australia



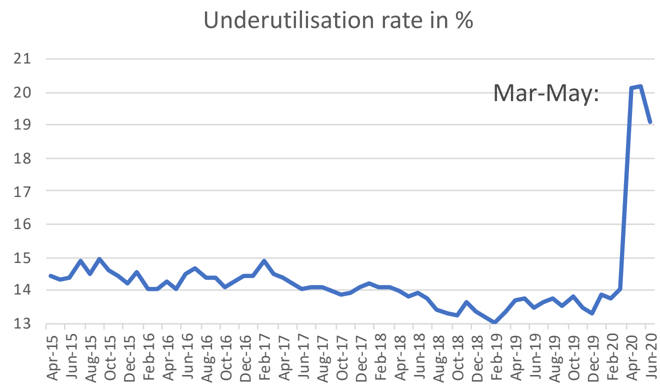
(a) Employed persons ('000)



(b) Unemployed persons ('000)

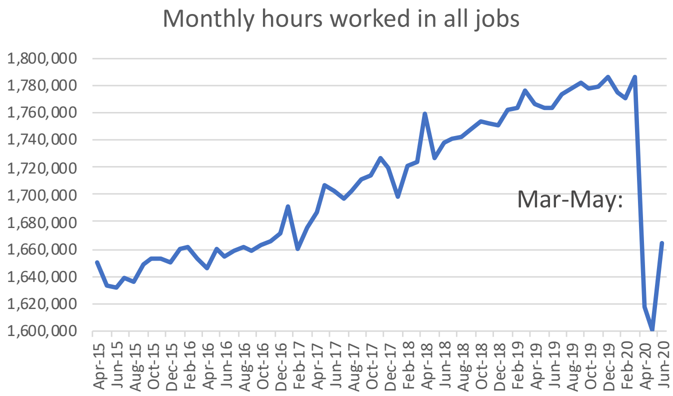


(c) Unemployment rate in %

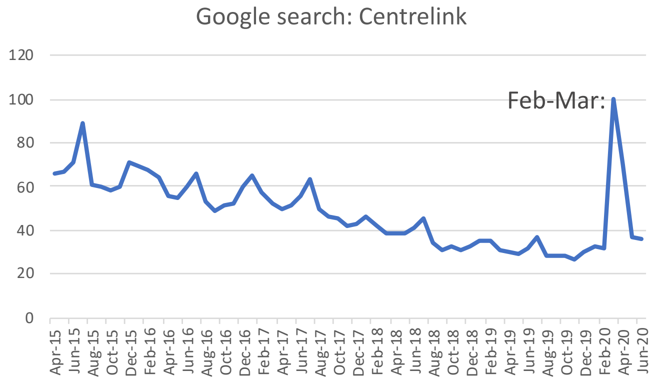


(d) Underutilisation in %

technical services (9%), manufacturing (9%), retail trade (8%), and transport, postal and warehousing (8%) (see Risse, 2020).



(e) Monthly hours worked in all jobs



(f) Google search for *Centrelink*

Note: Data from ABS Labour Force Australia Cat. No. 6202.0.

3. 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* [2]. 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 media, mainly via advertisements placed on Facebook, but also advertisements on Twitter and Instagram. Some responses were received from persons outside Australia, which for the purposes of this paper, were dropped. The final analysis sample as of July 7, 2020 includes 2,325 Australian residents who indicated that they were at least 18 years of age. To make the sample representative of the general Australian population, we constructed and applied population weights based on age and gender population data available from the Australian Bureau of Statistics (ABS, 2019). All analyses reported are population weighted.

3.1 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*

[2] 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).

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.

Table 1 lists the individual questions from our scale as well as their possible responses. 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.[3]

Table 1: Financial wellbeing items

Item	Responses
How well do the following statements describe you or your situation?	
1. I can enjoy life because of the way I'm managing my money.	0 - Not at all 1 - Very little 2 - Somewhat 3 - Very well 4 - Completely
2. I could handle a major unexpected expense.	
When it comes to how you think and feel about your finances, please indicate the extent to which you agree or disagree with the following statements:	
3. I feel on top of my day to day finances.	0 - Disagree strongly 1 - Disagree 2 - Neither agree/disagree 3 - Agree 4 - Agree strongly
4. I am comfortable with my current levels of spending relative to the funds I have coming in.	
5. I am on track to have enough money to provide for my financial needs in the future.	

3 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 well-being score.

Figure A1 in the Appendix shows for each of the underlying subcomponents of financial wellbeing the proportion of people who selected each potential 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. 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.

3.2 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"

A significant proportion of people in the sample report that they experienced one of these labour market shocks due to COVID-19: 32% had a reduction in work hours, 29% a reduction in wages/salaries, 16% loss of employment or business closure and 16% 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[4]. 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).[5] We combine the shocks of entry into unemployment or applying for benefits to reflect the Australian "JobSeeker" population.

We consider the association with financial wellbeing of each of the two labour market shocks individually, and also of whether a person has experienced either of these shocks. Each of these individual shock indicators are included as separate dummy regressors, equal to one if a respondent has experienced the shock as a direct result of COVID-19, and zero otherwise. Additional demographic controls were also included, which include the respondent's age group, gender, occupation field, household size and Australian state. In addition, our models include 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 breaks down the prevalence of the different labour market shocks experienced across the various groups in the sample. For instance, while 30% of individuals in 1- or 2-person households experienced a COVID-19 related labour market shock, 40% of 5- and 38% of 6- or more person households experienced one of the shocks. There are some clear gender differences, with a greater proportion of salary reductions reported by women (30% versus 21%) and also a greater proportion of lost jobs (26% versus 18%). On average 37% of women have experienced at least one labour market shock, but only 26% of men. In terms of age, the highest proportions of labour market shocks were among the 18-24 age group. Almost half (44%) of those in this age group experienced at least one labour market shock. There are notable differences across employment status and occupation. For example, some 70% of labourers and 60% of sales workers have experienced at least one shock, whilst only about one fifth of Managers and Professionals experienced a shock.

[4] See https://treasury.gov.au/coronavirus for further details.

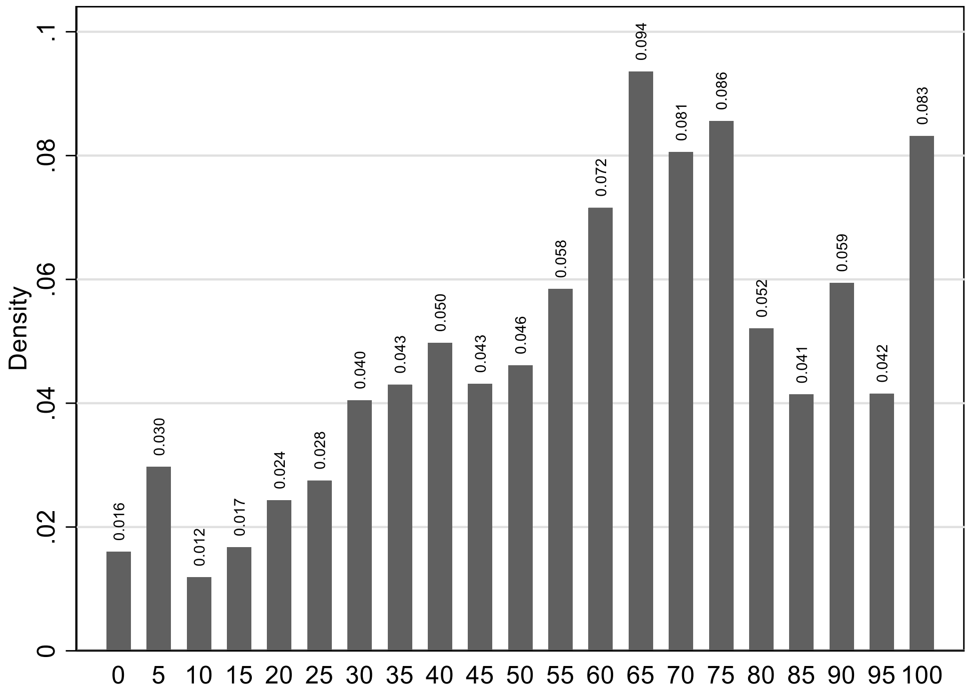
[5] Of the 35% who experience either a salary reduction or a reduction in work hours, the vast majority of this subgroup (74.3%) experienced both shocks simultaneously due to COVID-19. Rather than investigating the impact of two shocks separately, that affect mostly the same population, we focus on the 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.

While the labour market impacts of the pandemic seem to be felt across all demographic groups, they seem to be felt even more by women, the young, those in larger households (likely families with several children) and those working as sales workers and labourers.

Figure 1 depicts the factual distribution of financial wellbeing (a) as observed and (b) differentiated by “observed” versus “treated” status with respect to having experienced “any COVID-19 labour market shock”. The largest mass of the distribution in (a) is between 55 and 75 on the financial wellbeing scale of 0-100[6]. This picture changes dramatically when examining (b). Here we compare the observed distribution with the treated distribution and see that the mass of the distribution has moved leftward for those treated, i.e. having experienced a COVID-19 related labour market shock.

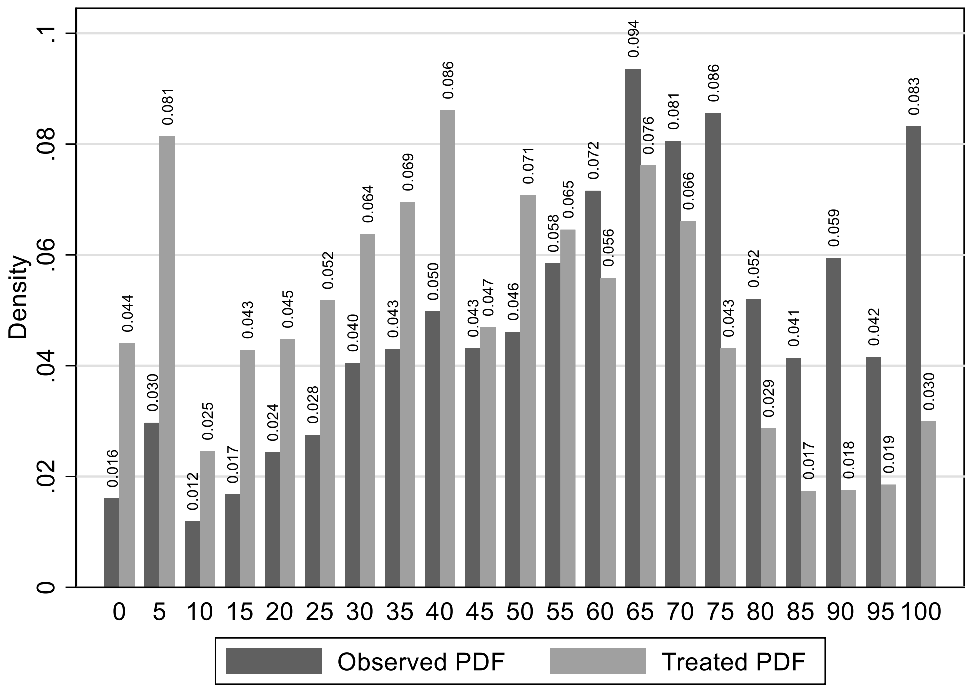
Figure 1: Distribution of Financial Wellbeing (FWB)

(a) Overall as Observed



[6] 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.

(b) Observed and Treated (Any COVID-19 Shock)



Note: Figure 1(a) displays the observed probability density function (PDF) of financial wellbeing. Figure 1(b) compares the distributional information of Figure 1(a) (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.

The histogram bars of the treated, between financial wellbeing levels 0-40, increase dramatically indicating that those having experienced these labour market shocks have substantially lower levels of financial wellbeing in the lower end of the distribution. Equally so, the treated are much less likely to be found in the higher end of the financial wellbeing distribution.

4. Empirical Strategy

4.1 Average associations

We apply a range of econometric methods to explore the potential association of COVID-19 related labour market shocks with Australians' financial wellbeing. First, we estimate standard linear OLS models for financial wellbeing in which we regress financial wellbeing, FWB_{it}, on each of the COVID-19 related labour market shocks, $Shock_{it}$, in separate regressions:

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

where $Shock_{it}$ 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, (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 ε_{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 that account for these potential biases. Still, it is still possible that there are other unobservables that might make certain groups of people more at risk of experiencing a COVID-19 related labour market shock while at the same time impacting on individuals' financial wellbeing. Because of this, we refrain from interpreting $\hat{\beta}$ as causal effects in equation (1), yet we still think that the results are informative. If we find strong negative associations between COVID-19 related labour market shocks and financial wellbeing, it indicates 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 of 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.

Another important point to make is that likely everyone's financial wellbeing is affected by the uncertainties introduced by the pandemic, not just financial wellbeing of those who directly experienced a labour market shock. We thus compare financial wellbeing of those who experienced a shock with levels of financial wellbeing that might already be lower than usual due to the uncertainties introduced by the pandemic, leading to a potential underestimation of the effects of COVID-19 induced labour market shocks.

4.2 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 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 β coefficient in equation (1). We implement the Altonji et al. (2005) and Oster (2019) calculations.[7] For a coefficient of negative value, the lower bound β_0 is calculated on the basis that the proportional degree of selection on unobservables to selection on observables is 0 (δ = 0) and is therefore equivalent to our estimate for β, while the upper bound β_1 is calculated on the basis that the amount of selection on unobservables is equal to selection on observables (δ = 1). This is generally viewed as a reasonable upper bound under the two-part assumption that the observables chosen act as a "random sample" of all outcome determinants and that the number of observables and unobserved determinants is relatively large. The second part of this assumption is easily justified in our case: there are likely very many determinants of financial wellbeing and in any one survey we are only likely to measure few of them. The first part of the assumption is more contentious in our case. Yet in our empirical design we actively did not guide our control variable choice by choosing 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, in fact, 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.

[7] Emily Oster provides a Stata ADO file called "psacalc.ado" which provides the unobservables/observables factor δ and upper bound β estimations after an OLS regression.

4.3 Quantile Effects

Whilst the above OLS 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 substantially lower financial wellbeing FWB_{it} as compared to the average association, or indeed, the lower levels that somebody experiencing a COVID-19 related shock already high up in the FWB_{it} distribution might experience. Though the average associations are of importance, for targeted policy recommendations, it is likely that the relationship in the left tail of the FWB_{it} distribution is more pronounced and should receive special attention.

Thus, we 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 use the *unconditional* quantile estimator of Firpo, Fortin, and Lemieux (2009)[8] that allows us to produce *unconditional* quantile estimates, which have the interpretation of the size of the association at a given point in the FWB_{it} distribution.

We examine the coefficients of the $Shock_{it}$ variables at the 10-, 25-, 50- (median), and 75-and 90-percentile of the FWB_{it} distribution. We also contrast and compare these quantile regression results to the OLS results to identify variability of effects over the FWB_{it} distribution.

4.4 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 assess these questions properly, we apply the well-known DiNardo, Fortin and Lemieux (1996) decomposition approach to financial wellbeing. 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.

8 We use Fernando Rios-Avila's code contained in the Stata ADO "rifhdreg.ado", which calculates re-centered influence function regression.

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

$$Prob(Shock_{it}) = \Phi(Demog_{it}\beta + \varepsilon_{it}) \qquad (3a)$$

$$DFL_w = (1 - \widehat{Shock_{it}})/\widehat{Shock_{it}} \qquad \text{if } Shock_{it} = 1 \qquad (3b)$$

$$kdensity\ FWB_{it}\ [weight = 1] \qquad \text{if } Shock_{it} = 1 \qquad (3c)$$

$$kdensity\ FWB_{it}\ [weight = DFL_w] \qquad \text{if } Shock_{it} = 1 \qquad (3d)$$

In the first step we estimate a non-linear binary probit probability model of $Shock_{it}$, where *Prob* denotes the probability and Φ is the cumulative distribution function of the standard normal distribution, using the demographic controls as explanatory variables as in (3a) to construct the DiNardo et al. (1996) counterfactual weight DFL_w in (3b). We compare the factual density of FWB_{it} with $Shock_{it} = 1$ in (3c) with the *counterfactual* density of FWB_{it} with $Shock_{it} = 1$ weighted by DFL_w in (3d), 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 Φ (CDF) and calculate measures of inequality/dispersion to assess the extent to which financial wellbeing inequality is associated with $Shock_{it}$. 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_{it} 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.

In previous analyses, we have treated the FWB_{it} distribution as a continuous variable. In fact, as shown in Figure 1, FWB_{it} contains discrete values 0 through 100 in steps of 5. To address the issue of the discrete nature of the values, we implement distribution regression (see Chernozhukov et al. 2013, 2020a; Chernozhukov et al. 2020b; and Van Kerm 2015 for further details on distribution regression). We start with the original OLS regression in (1), with the same regressors:

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

and replace the outcome variable FWB_{it} with a series of dummy variables $fwbR_{it}$ such that:

$fwb0_{it} = 1\ if\ FWB_{it} > 0\ (and, 0\ not),$

$fwb5_{it} = 1\ if\ FWB_{it} > 5\ (and, 0\ not),\ \ldots,$

$fwbR_{it} = 1\ if\ FWB_{it} > R\ (and, 0\ not),$ for $R \geq 10\ \&\ R < 90$

$fwb95_{it} = 1\ if\ FWB_{it} > 95\ (and, 0\ not):$

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:

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

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

An interesting property of distribution regression is that summing up the respective linear probability model coefficients over the entire FWB_{it} distribution gives *exactly* the overall OLS estimate[9] in (1), but we see the influence of the explanatory variables at *every point* in the outcome variable distribution.

Quantile 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. As we have seen there are substantial quantile effects at the 10th and 25th percentile. However, if there are relatively few individuals actually situated at these points in the distribution (see Figure 1), we may wish to relativise the importance of these effects. There could be much smaller effects for each value in the middle of the distribution of the financial wellbeing variable FWB_{it}, but if far more people are sitting at these points in the distribution, the overall influence on the entire

[9] 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.

distribution may be the greatest. We see this potential in Figure 1(a) where the values of FWB_{it} = 60, 70, 75 are the peaks of the distribution.

After having estimated the set of 20 linear probability models, we can simulate a counterfactual distribution for the treated population. 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 wellbeing, in which we remove the association with $Shock_{it}$ at each discrete value of the FWB_{it} distribution. For those treated and for each of the respective observed and counterfactual distributions, we calculate the Gini inequality coefficient, the values of financial wellbeing at the median (50th percentile), the 10th percentile and the 90th percentile.

5. Results

5.1 Average effects and effects over the distribution

The main regression results of the estimates of interest are presented in Table 2.[10] We report the OLS estimates in 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 10th, 25th, 50th, 75th and 90th percentiles are reported in columns (2)-(6). In all estimations we control for the demographic characteristics, labour market status and occupation as well as region fixed effects and a week of the year time trend.

Considering the OLS 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 17.8-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

[10] 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.

the magnitude of the associated shock, so we will focus here on primarily 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, 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 2, Panel A). 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 would have to be quite high, between 1.84 to 2.77 times higher than selection on the observables 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.

Although the average associations of financial wellbeing with COVID-19 labour market shocks are large, the OLS estimates obscure important differences across the financial wellbeing distribution. Specifically, examining the entire financial wellbeing distribution, in the quantile regression results (Table 2, 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_{th} and 25_{th} percentiles. The relationship between labour market shocks and financial wellbeing for those in the 90_{th} 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 increase in magnitude as we move leftward in the financial wellbeing distribution.

Table 2: COVID-19 Labour Market Shocks and Financial Wellbeing

Variable	Mean	Q10	Q25	Q50	Q75	Q90
	(1)	(2)	(3)	(4)	(5)	(6)
A.						
Salary & Hours	-18.821***	-24.621***	-30.739***	-19.900***	-14.336***	-7.227***
	(1.915)	(4.495)	(3.770)	(1.986)	(2.052)	(1.776)
[Bounds: β_0, β_1]	[-18.821, -15.90]	-	-	-	-	-
δ req'd for $\beta = 0$	2.77	-	-	-	-	-
B.						
UE or Benefits	-15.808***	-21.463***	-21.794***	-14.775***	-15.119***	-8.829***
	(1.915)	(4.458)	(4.040)	(2.363)	(2.080)	(1.550)
[Bounds: β_0, β_1]	[-15.808, -10.2]	-	-	-	-	-
δ req'd for $\beta = 0$	1.84	-	-	-	-	-
C.						
Any Shocks	-17.860***	-23.322***	-27.837***	-17.490***	-15.547***	-7.868***
	(1.876)	(4.179)	(3.696)	(2.102)	(2.086)	(1.752)
[Bounds: β_0, β_1]	[-17.860, -12.8]	-	-	-	-	-
δ req'd for $\beta = 0$	1.93	-	-	-	-	-
Demographic controls	✓	✓	✓	✓	✓	✓
Labour market status:						
Not working	✓	✓	✓	✓	✓	✓
Occupation FE	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓
Week Time Trend	✓	✓	✓	✓	✓	✓

Note: * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses. Each panel 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 $R_{max} = 1.3(R_2)$, where R_2 is from the OLS regressions with all controls. The lower bound β_0 is calculated on the basis that the proportional degree of selection on unobservables to selection on observables is 0 (δ=0) and is therefore equivalent to our estimate for β, while the upper bound β_1 is calculated on the basis that the amount of selection on unobservables is equal to selection on observables (δ=1). The estimated δ suggests that there must be δ 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.

In Table 2, Panel A for example, the association with a *salary reduction* is strongest for the 25th percentile with a drop of 30.7 points, whereas the 75th 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 75th percentile, as opposed to the 25th 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 A) compared to unemployment and having to apply for benefits (Panel B), as well as having experienced any shocks (Panel C). Appendix Figure A2 shows the estimated coefficients of having experienced *any shocks* (Panel C) of the unconditional quantile regression at various slices of the financial wellbeing distribution as well as at the (OLS) mean 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 Table 3, in which we compare the distributional ranges, the widest 10-50-90 and the slightly narrower 25-50-75.[11] In general, all three of the main labour market shocks in Table 3, Panels A-C 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 Table 3, Panel C, we note that the difference between the 90th percentile and the 10th percentile of the financial wellbeing distribution is 15.5 points (and statistically significant). In the lower half of the distribution, the distance between the 10th 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, Table 3 shows 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 focus solely on the effect of experiencing any COVID-19 labor market shock since our estimates are so similar across panels A and B of Tables 2 and 3.

[11] Full corresponding estimation results are shown in Table A4.

Table 3: Financial Wellbeing: Inter-percentile Ranges

Variable	I(90-10)	I(50-10)	I(90-50)	I(75-25)	I(50-25)	I(75-50)
	(1)	(2)	(3)	(4)	(5)	(6)
A.						
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)
B.						
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)
C.						
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)

Note: * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses. The table shows the inter-percentile ranges at two points in the financial wellbeing distribution, e.g. the difference in financial wellbeing at the 90th percentile compared to that at the 10th 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 Table 2. R^2 ranges from 0.119 for I(90-10) to 0.031 for I(75-50).

5.2 Counterfactual distributional analysis

Turning to the counterfactual distributional DiNardo et al. (1996) analysis[12], we examine the distributional associations of financial wellbeing with $Shock_{it}$=1 with respect to having experienced a COVID-19 related reduction in earnings and hours worked, or entry into unemployment or having filed for unemployment benefits. We present the results both graphically in Figure 2 as well as numerically in Table 4 (with first step results in Table A5 in the Appendix).

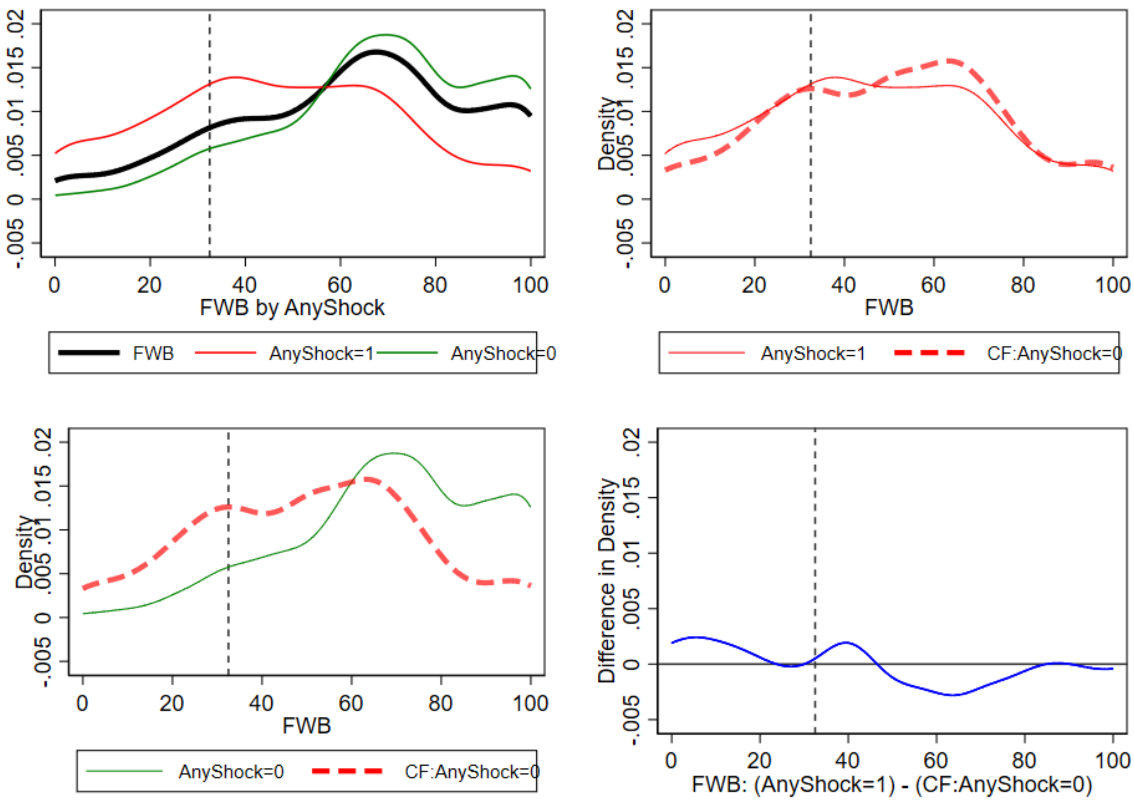
The top left graph of Figure 2 displays the factual probability density functions (population/sample weighted) of: the overall financial wellbeing distribution (thick black line), the factual financial wellbeing density for those who experienced any labour market shocks (red line) and the factual financial wellbeing density for those who did not experience any labour market shocks (green line). We clearly see that the distribution (in red) is shifted to the left for those who experienced a COVID-19 related labour market shock. The top right of Figure 2 shows again the observed distribution of financial wellbeing (solid line) for those having indeed experienced shocks compared to the counterfactual distribution of financial wellbeing for those who experienced a shock (dashed line) weighted not to have experienced shocks. The counterfactual distribution seems to have more mass at the right end that the factual distribution. The bottom right of Figure 2 displays the difference in density of the two top right densities: experienced shocks *minus* the counterfactual weighted not to have experienced shocks. We see that any labour shock has

[12] We use the Stata DO file code "dfl8.do" provided by Nicole Fortin to calculate the DFL (1996) counterfactual analysis and augment this for sample weights.

increased the mass on the 0-25 (very poor-off) range of financial wellbeing, as well as in the 30 to 50 range. In contrast, there is much less mass in the range 50 to 80 (relatively well-off) in the financial wellbeing scale of 0 to 100. The treatment distribution (solid red line) is flatter and more disperse as compared to the more compact counterfactual distribution (dashed red line), indicating higher level of inequality associated with treatment. For completeness, the bottom left part of Figure 2 compares the observed distribution of financial wellbeing for those not having experienced any shocks (thin green line) with the counterfactual distribution of financial wellbeing for those who experienced a shock weighted not to have experienced such shocks. It is clear that the distribution of financial wellbeing for those who have factually not experienced the shock is not at all indicative of the counterfactual distribution for those who factually experienced a shock, indicating the relevance of the DFL decomposition.

These important conclusions are seen numerically as well in Table 4 where we compare observed distributions with counterfactual distributions of financial wellbeing. In Panel A of Table 4, 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 2: 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 for those *not* having experienced AnyShock (green line) and for the counterfactual 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.

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 0.246[13] for those counterfactually not having experienced any COVID-19 labour market shocks. This increases to 0.284 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).

[13] 50% of the median FWB value of 65 is 32.5.

Table 4: DiNardo et al. (1996) FWB Decompositions by COVID-19 Shocks

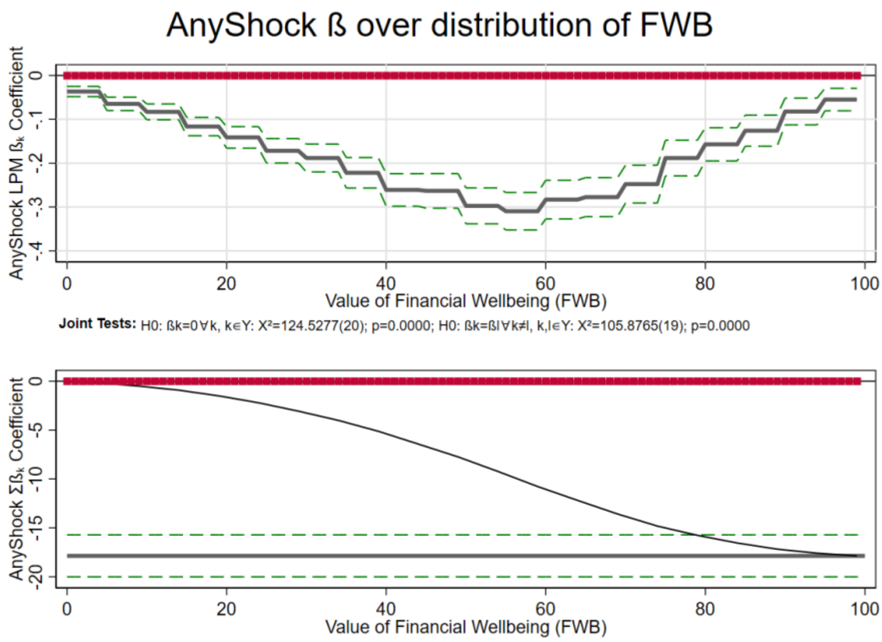
Distribution	Mean FWB Mean	Mean FWB Std.	HCR 50% (Med)	Percentiles FWB 25%	Percentiles FWB 50%	Percentiles FWB 75%	Inter-percentile Range 75%-25%	Inter-percentile Range 75%-50%	Inter-percentile Range 50%-25%
A.									
FWB: As observed	56.46	23.406	0.143	44.541	64.94	81.688	37.147	16.746	20.400
B.									
FWB | Any Shock	44.58	23.418	0.284	29.883	48.63	68.160	38.278	19.530	18.747
FWB: CF No Shock	47.84	22.579	0.246	32.884	52.54	68.987	36.103	16.442	19.661
FWB | No Shock	62.06	20.851	0.076	55.111	70.33	86.298	31.187	15.963	15.224

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.

As a robustness check, we also check the sensitivity of our distributional results by addressing the discrete nature of the financial wellbeing measure, rather than assuming a continuous outcome variable. We do this by examining distribution effects using distribution regression as in Chernozhukov et al. (2013). The top panel of Figure 3 displays all of the point estimates for 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 panel, 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 (χ^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 pane of Figure 3 (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 (χ^2=105.9 with 19 degrees of freedom). The top panel of Figure 3 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.

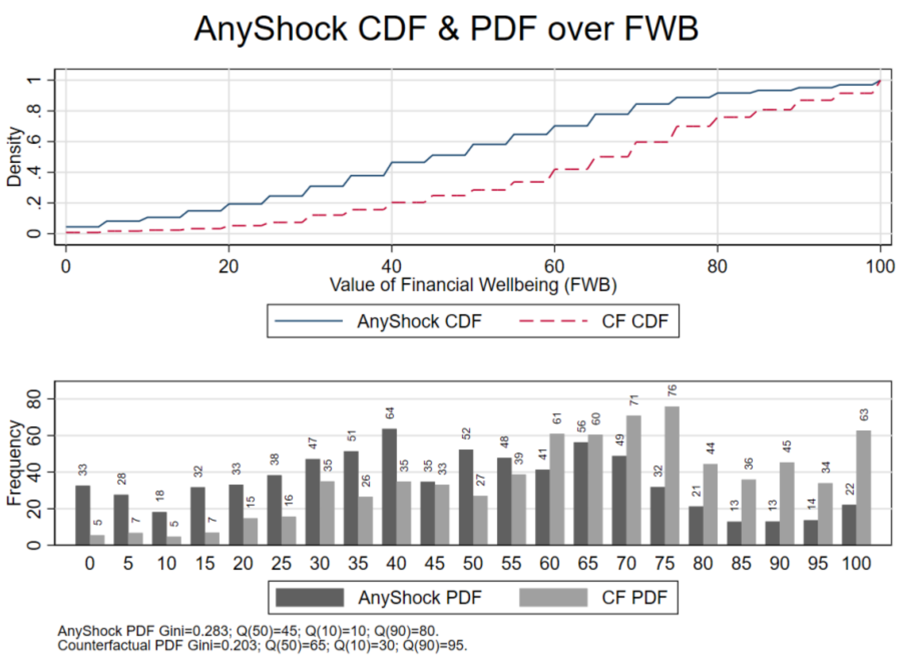
Figure 3: Distribution Regression: Any COVID19 Shock



Note: The top panel 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 (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. Hypothesis testing of the coefficients jointly equalling zero is soundly rejected, as well as the test of equality of the coefficients themselves. From this we can conclude that there are indeed distributional differences in the association of *AnyShock* with financial wellbeing over the distribution of financial wellbeing. 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).

In Figure 4, 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) and the cumulative density functions (CDFs) of the observed and counterfactual distributions.

Figure 4: Distribution Regression: Treated and Counterfactual Densities



Note: The top panel 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.

In the bottom panel of Figure 4, 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 4, 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 below the bottom panel of Figure 4, in which distributional statistics are reported. For those treated and for each of the respective observed and counterfactual distributions, we calculate the Gini inequality coefficient, the values of financial wellbeing at the median (50th percentile), the 10th percentile and the 90th percentile. 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 effect of -18.2 points on the financial wellbeing, there are substantial and significant distributional associations differing by position in the financial wellbeing distribution.

6. 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.

We focus on financial wellbeing rather than income, as it gives a more complete picture on the actual financial stressors people feel during the pandemic, as one does not have to be rich to achieve high levels of financial wellbeing, and similarly one does not have to be poor to have low levels of financial wellbeing. Ultimately, many people in today's world do not strive for maximum income, nor is a high income necessary to live a comfortable and fulfilled life. Rather, many individuals aim to achieve and maintain financial wellbeing. Financial wellbeing captures functional, situational as well as temporal components: It measures the extent to which individuals 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.

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. During the pandemic, we observe a large proportion of Australians experiencing a labour market shock due to COVID-19: 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. A significant proportion of Australians report having troubles with their financial wellbeing: For example, 31% report not to have enough money to provide for their financial needs in the future, 25% could not handle a major unexpected expense at all or very little, 19% are not comfortable with their current level of spending, 17% do not feel on top of their finances, and 15% report that they cannot enjoy life at all or very little because of the way they are managing their money.

Controlling for a range of demographic characteristics as well as labour market status including occupational information, region fixed effects and a week of the year time trend, we show that having experienced any of the examined COVID-19 related labour market shocks is significantly associated with a 29% reduction in financial wellbeing (or 17.8-points on the 0-100 financial wellbeing scale). A bounds-analysis shows that selection on unobservables would have to be twice as high as selection on observables to render this effect insignificant. This suggests that 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. In reality, it is likely that our estimated effects may capture both a causal effect as well as an association with unobservables. Either way, it points to substantial inequalities in the experience of the pandemic, be it in terms of exposure to labour market shocks by those who are already “doing it tough” with very low financial wellbeing or in terms of the felt impact with regard to financial wellbeing due to a COVID-19 related labour market shock.

In addition, we identify large inequalities across the financial wellbeing distribution. Unconditional quantile effects using re-centered influence functions (RIF) reveal that the relationship is strongest at the bottom of the distribution: for the 25th percentile an experience of any of the shocks is associated with a drop of 28 points on the 0-100 financial wellbeing scale, whereas the 75th percentile experiences only a 16-point drop. A counterfactual distributional DiNardo et al. (1996) analysis demonstrates that the COVID-19 labour market shocks are associated with shifting the mass of the financial wellbeing distribution leftward, making all in general worse off and increasing the dispersion of financial wellbeing, which necessarily reflects higher levels of inequality in financial wellbeing. The shocks are associated with increasing the mass left of 50% of the median financial wellbeing value, called the head-count-ratio (HCR), analogous to the “relative poor” in the earnings inequality literature. The HCR, i.e. the share of the distribution that is situated to the left of the 50% of the median FWB value, is 0.246 for those counterfactually not having experienced any COVID-19 labour market shocks. This increases to 0.284 for those experiencing any labour market shock. Checking the sensitivity of our distributional results by estimating distribution regressions (Chernozhukov et al. 2013), which in contrast to DFL, addresses the discrete nature of the financial wellbeing measure, 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.

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. Those having filed for JobSeeker benefits can only receive a maximum of $1300/fortnight which for many is not likely a large percentage of their previous earnings. Thus, JobSeekers have likely experienced a large drop in earnings/benefits despite their ongoing financial commitments. In the past, those being made redundant could search for other employment, and in a period of 20+ years of continuous growth in Australia, finding new employment quickly was relatively probable. However, against this backdrop of COVID-19, those having lost employment experience dramatically reduced outside opportunities.

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 unemployment benefits. Thus, while the underemployed due to COVID-19 are at least still “employed”, their financial wellbeing is just as precarious as those explicitly unemployed due to COVID-19. It is likely that these individuals, who generally would receive JobKeeper benefits, are aware of their precarious position, despite their wage subsidy, and thus report substantially lower levels of financial wellbeing. Despite the current extension of JobKeeper payments, it is also possible that discussions by the government when to finally cease the JobKeeper payments have increased uncertainties around future financial wellbeing.

It seems that those low in financial wellbeing are hit doubly hard: They are potentially more exposed to experiencing a COVID-19 related labour market shocks, and additionally the association between the shock and financial wellbeing is much stronger for those at the lower end of the financial wellbeing distribution. As such, it seems that there is a significant risk that inequality in financial wellbeing will increase in the near future, with a significant proportion of people who feel that they won’t be able to enjoy life because of their financial situation (currently already

15% report that they can enjoy life very little or not at all due to the way they are managing their money).

For real improvements in financial wellbeing, it will be crucial that underemployment is reduced, that Australians regain much higher levels of *real employment*, that the confidence of labour force participants in their labour market prospects is restored, and that uncertainties with respect to financial wellbeing are buffered by a social safety net that Australians have confidence in and feel they can rely on. This is particularly important for those who are already “doing it tough” in terms of financial wellbeing.

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Appendix Tables

Table A1: Weighted descriptive statistics

	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 A2: Descriptive statistics of COVID-19 shocks by covariates

	Size	Salary reduction		Unemployment		Any shock	
	%	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 status + Occupation							
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
Personal 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

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

Table A3: Financial Wellbeing: Any COVID-19 shocks

	(1) OLS	(2) Q(10)	(3) Q(25)	(4) Q(50)	(5) Q(75)	(6) Q(90)
Week of Year	0.298	0.357	0.771*	0.225	0.344	-0.181
	(0.218)	(0.394)	(0.390)	(0.329)	(0.331)	(0.258)
Household size	0.057	-0.198	0.677	-0.056	0.266	-0.997
	(0.644)	(1.258)	(1.268)	(0.785)	(0.911)	(0.784)
Male	3.345	2.869	2.548	1.869	4.757	3.493
	(1.801)	(3.383)	(3.270)	(2.412)	(2.646)	(2.321)
Age Group:						
[2] 18-24	-4.853	-10.947	-11.010	-2.994	-2.278	-1.955
	(3.198)	(7.077)	(6.506)	(4.096)	(4.910)	(4.042)
[3] 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)
[4] 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)
[5] 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)
[6] 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:						
[0] 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)
[10] 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)
[20] 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)
[30] 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)
[40] 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)
[50] 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)
[60] 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)
[70] Machinery Ops	-4.867	-12.876	6.808	3.710	-6.325	-10.688
	(7.114)	(16.631)	(10.743)	(7.907)	(8.289)	(5.612)
[80] Labourers	-2.719	22.959**	-14.953	-3.677	-16.173***	-7.323**
	(3.759)	(7.462)	(13.711)	(7.008)	(4.566)	(2.728)
[98] Other	-3.416	-6.467	-6.275	-4.776*	-2.881	-1.387
	(1.767)	(3.666)	(3.544)	(2.322)	(2.539)	(2.252)
State:						
[1] ACT	2.524	-6.788	0.839	9.258**	7.769	10.244
	(4.152)	(5.064)	(5.021)	(3.506)	(9.320)	(10.909)
[2] NSW	-0.577	2.885	-3.627	-3.113	-0.106	-1.879
	(1.387)	(2.237)	(2.812)	(1.994)	(2.421)	(1.949)
[3] 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)
[4] QLD	0.535	0.339	-1.826	0.829	1.594	3.120
	(2.105)	(2.722)	(3.352)	(2.381)	(3.504)	(3.625)
[5] 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)
[6] 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)
[7] 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)
[8] 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)
C19 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_2	.212	.119	.175	.135	.0915	.0615
N	2325	2325	2325	2325	2325	2325
Bound	-12.8					
Delta	1.93					

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: The shock variable coefficient provides the upper bound estimate. 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. The lower bound estimate is calculated on the basis of a <delta> equal to 1, such that amount of selection on unobservables is equal to selection on observables.

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

	(1) I(90-10)	(2) I(50-10)	(3) I(90-50)	(4) I(75-25)	(5) I(50-25)	(6) 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:						
[2] 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)
[3] 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)
[4] 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)
[5] 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)
[6] 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:						
[0] 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)
[10] Managers	0.341	-2.170	2.511	-0.486	-0.768	0.282
	(4.551)	(3.016)	(3.893)	(4.111)	(2.896)	(3.128)
[20] Professionals	-1.937	1.350	-3.287*	-1.126	-2.068	0.942
	(2.010)	(1.787)	(1.467)	(1.914)	(1.446)	(1.320)
[30] Trades Workers	12.543	0.922	11.621*	-4.058	-5.587	1.529
	(8.039)	(7.097)	(5.902)	(7.586)	(6.160)	(5.357)
[40] Personal Service	10.892	3.612	7.280	4.287	0.620	3.667
	(9.914)	(8.219)	(4.101)	(5.061)	(4.146)	(2.917)
[50] Clerical	-14.722***	-8.653**	-6.069*	-7.995*	-2.206	-5.789
	(2.600)	(3.113)	(2.811)	(3.738)	(2.557)	(2.986)
[60] Sales	-3.676	-4.600	0.924	-6.786	-1.983	-4.803
	(8.674)	(8.103)	(5.678)	(8.294)	(6.042)	(5.546)
[70] Machinery Ops	2.189	16.586	-14.398	-13.133	-3.098	-10.035
	(16.709)	(13.600)	(8.352)	(11.167)	(8.572)	(7.905)
[80] Labourers	-30.283***	-26.637*	-3.646	-1.221	11.275	-12.496
	(7.470)	(10.428)	(8.419)	(16.075)	(8.526)	(9.836)
[98] Other	5.080	1.692	3.389	3.394	1.499	1.895
	(4.234)	(3.897)	(2.654)	(3.985)	(3.281)	(2.370)
State:						
[1] ACT	17.032	16.046***	0.987	6.930	8.419**	-1.488
	(11.348)	(4.790)	(10.583)	(9.681)	(3.151)	(9.184)
[2] NSW	-4.764	-5.998*	1.234	3.521	0.514	3.006
	(2.925)	(2.810)	(2.293)	(3.129)	(2.471)	(1.951)
[3] NT	0.626	-5.930	6.556	6.420	1.317	5.103
	(14.457)	(9.969)	(10.064)	(11.859)	(9.171)	(7.876)
[4] QLD	2.780	0.490	2.290	3.420	2.655	0.765
	(4.303)	(3.248)	(3.396)	(3.939)	(2.706)	(2.999)
[5] SA	13.723	11.894	1.829	9.979	7.935	2.045
	(10.327)	(9.012)	(4.499)	(6.518)	(4.800)	(3.586)
[6] 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)
[7] 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)
[8] 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_2	0.0574	0.0329	0.0410	0.0438	0.0529	0.0143

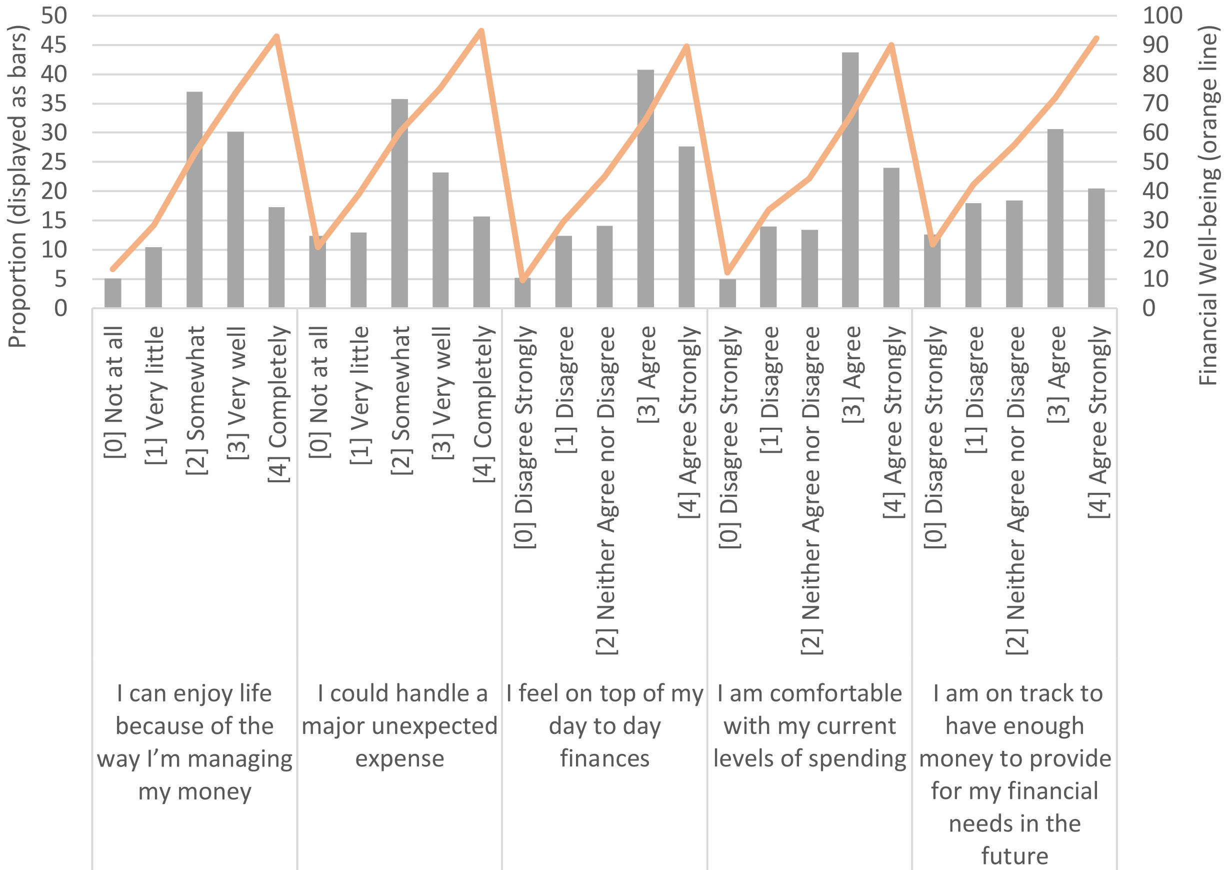
Note: N=2325. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A5: Financial Wellbeing: DFL Decomposition: 1st Stage

Variable	*β*	Marginal Effect
Week of Year	0.025**	0.008**
	(0.009)	(0.003)
Household size	0.029	0.009
	(0.022)	(0.007)
Male	-0.209**	-0.064**
	(0.065)	(0.020)
Age Group:		
[2] 18-24	--	---
[3] 25-34	-0.251*	-0.075*
	(0.112)	(0.035)
[4] 35-44	0.116	0.038
	(0.110)	(0.035)
[5] 45-54	-0.183	-0.056
	(0.113)	(0.035)
[6] 55-64	0.077	0.025
	(0.116)	(0.037)
Occupation:		
[0] Not employed	--	--
[10] Managers	-1.121***	-0.406***
	(0.131)	(0.044)
[20] Professionals	-1.276***	-0.449***
	(0.108)	(0.038)
[30] Trades Workers	-0.821***	-0.308***
	(0.155)	(0.055)
[40] Personal Service	-0.843***	-0.316***
	(0.149)	(0.053)
[50] Clerical	-1.030***	-0.378***
	(0.146)	(0.049)
[60] Sales	-0.220	-0.082
	(0.161)	(0.060)
[70] Machinery Ops	-0.554*	-0.210*
	(0.222)	(0.084)
[80] Labourers	0.154	0.054
	(0.242)	(0.083)
[98] Other	-0.441***	-0.167***
	(0.124)	(0.046)
State:		
[1] ACT	--	--
[2] NSW	0.628*	0.167**
	(0.260)	(0.057)
[3] NT	0.783	0.217
	(0.428)	(0.127)
[4] QLD	0.535*	0.139*
	(0.266)	(0.059)
[5] SA	0.588*	0.155*
	(0.279)	(0.065)
[6] TAS	0.653*	0.175*
	(0.292)	(0.071)
[7] VIC	0.636*	0.170**
	(0.256)	(0.055)
[8] WA	0.378	0.093
	(0.274)	(0.061)
Constant	-0.660	
	(0.355)	

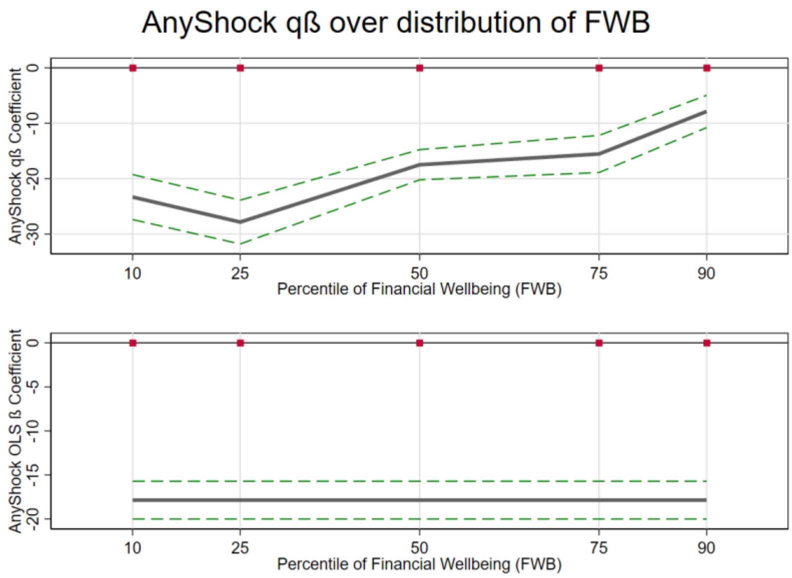
Note: N=2325. Probit non-linear regression.
* p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses.
Reference categories: Male, Age 18-24, not in employment.

Figure A1: 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 A2: Unconditional Quantile Regression: Coefficients over Financial Wellbeing Distribution



Note: The top panel shows the estimated regression coefficients (Table 2, Panel C) 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 (-17.8) which does not change over the distribution of financial wellbeing (black line). The quantile coefficient at the 25_{th} percentile (-27.8) is larger in absolute terms than the OLS estimate (-17.8) and at the 90_{th} 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.