I Z A Institute of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 13235

Modelling the Distributional Impact of the COVID-19 Crisis

Cathal O'Donoghue
Denisa M. Sologon
Iryna Kyzyma
John McHale

MAY 2020

I Z A Institute
of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 13235

Modelling the Distributional Impact of the COVID-19 Crisis

Cathal O'Donoghue
National University of Ireland and IZA

Denisa M. Sologon
Luxembourg Institute of Socio-Economic Research

Iryna Kyzyma
Luxembourg Institute of Socio-Economic Research and IZA

John McHale
National University of Ireland

MAY 2020

ISSN: 2365-9793

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Modelling the Distributional Impact of the COVID-19 Crisis*

Given the rapid spread of the COVID-19 virus, the State has had to respond rapidly and quite severely to flatten the curve and slow the spread of the virus. This has had significant implications for many aspects of life with differential impacts across the population. The lack of timely available data constrains the estimation of the scale and direction of recent changes in the income distribution, which in turn constrain policymakers seeking to monitor such developments. We overcome the lack of data by proposing a dynamic calibrated microsimulation approach to generate counterfactual income distributions as a function of more timely external data than is available in dated income surveys. We combine nowcasting methods using publicly available data and a household income generation model to perform the first calibrated simulation based upon actual data aiming to assess the distributional implications of the COVID-19 crisis in Ireland. We extend the standard definition of disposable income by adjusting for work-related expenditure, housing costs and capital losses. We find that market incomes decreased along the distribution of disposable income, but decreases in euro terms were more pronounced at the top than at the bottom. Despite this, inequality in market incomes as measured by the Gini coefficient increased over the crisis. Once we account for the decline in housing and work-related expenses, households situated among the bottom 70% of the distribution actually improved their financial situation on average, whereas losses are recorded for the top 30%.

JEL Classification: H23, C15

Keywords: COVID-19, distributional impact, microsimulation, nowcasting, income generation model, income distribution, fiscal policy, inequality, poverty

Corresponding author:
Denisa M. Sologon
Luxembourg Institute of Socio-Economic Research
11 Porte des Sciences
4366 Esch-sur-Alzette
Luxemburg
E-mail: Denisa.Sologon@liser.lu

* The Authors are grateful to the Irish Health Research Board and Irish Research Council for funding of this research.

Modelling the Distributional impact of the Covid-19 Crisis[1][2]

1. Introduction

The sudden appearance and global spread of the Covid-19 virus is doing enormous damage to public health and living standards. Recognising the significance of this new virus, States have responded rapidly with large-scale interventions to to slow the spread of the virus and limit the damage to incomes. As part of this response, policy makers across the world have moved to partially shut down their economies as a necessary public health measure to limit contacts and suppress transmission. This has had significant implications on many aspects of life with health, economic and social consequences being highly asymmetric, affecting different groups differently. The aim of this paper is to undertake a real-time analysis of the income distribution effects. . This analysis helps to identify who is most likely to suffer from loss of income, and can support a more effective/efficient targeting of income support measures and allow improved cost estimates of these measures.

The differing experiences of countries such as South Korea and Italy has shown the importance of early intervention. From an economic perspective, the policy response has had two main elements. First, physical gatherings to produce goods and services deemed non-essential have been largely shut down even as production in targeted health-related areas has expanded. And second, new in-employment and out-of-employment income support schemes have been put in place to ensure that household access to essential goods and services – and where possible continued formal links to employers– are maintained during the emergency. It is recognised that these policies will have major implications for public finances, but there is widespread acceptance that significant deficits are a necessary price for suppressing the spread of the virus while limiting economic damage provided borrowing capacity can be retained.

This is a distinctive crisis, expected to dwarf the financial crisis from 2008 (Baldwin & Weder di Mauro 2020) with a major cost in terms of health and human lives. Less dramatic in terms of its impacts on affected individuals, yet more pervasive, will be the economic cost to workers that become unemployed or lose (part of) their incomes. Public policy is at the forefront of the crisis applied 'timely, targeted and temporary' (Gaspar and Mauro 2020) with a huge potential to stabilise the economy during the crisis. Policy makers need to support the incomes of those adversely affected by the policy-imposed shutdown, especially given the speed with which the crisis has unfolded. This requires a timely understanding of those most affected by the containment measures or more at risk. In managing income distribution impacts (and associated fiscal costs) it is valuable to be able to assess the effects of different wage and unemployment support policies given the most up-to-date information on the labour market.

We are in a situation where there is lack of timely available data required to do appropriate policy analysis. There are constraints for estimating the scale and direction of recent changes in the income distribution, which in turn set constraints for policymakers seeking to monitor such developments. There are huge uncertainties about the budgetary costs and distributional impacts of the outbreak. Crisis management implies looking at these costs and distributional impacts starting now.

---

[1] The Authors are grateful to the Irish Health Research Board and Irish Research Council for funding of this research.
[2] Corresponding Author. Denisa.Sologon@liser.lu

We are proposing a calibrated simulation based upon actual data aiming to assess the distributional implications of the COVID-19 crisis in Ireland. In particular, we aim to identify those most likely to suffer from income losses, and how these losses are distributed in the society. These estimates provide policy makers the evidence-based input needed for designing effective/efficient targeting of income support measures. The earliest scenario analysis assessing the impact of the crisis is done by Beirne et al. (2020). Our work extends the literature by calibrating to actual real time reported impacts. Given the rapid development of the crisis, we are proposing a dynamic calibrated approach that looks at the actual income distribution at the start of the crisis and considers the full extent of the asymmetric unemployment shock, including reassessment of work-related expenditures (commuting and child-care), the distribution of COVID-19 cases by age and work status and the impact of mortgage repayments and changes in the distribution of holding shares and their value.

Apart from the conventional definition of household disposable equivalized income, we also consider an alternative definition by adjusting household disposable equivalized income for work-related, housing expenditures and some capital losses. By using this definition, we can identify real changes in the financial resources available for households during the crisis as compared to the period before. As we further show in the paper, a decrease in this expenditure during the crisis helped most individuals to maintain their disposable incomes at the pre-crisis level or even to increase them, which served as an important mitigation instrument for market income losses.

We overcome the data gap by using a "nowcasting" methodology based on an aligned or calibrated microsimulation approach to generate a counterfactual income distributions as a function of more timely external data than the underlying income survey (O'Donoghue and Sologon, 2020). We combine nowcasting methods using up-to-date data from live registers, official reports on the labour market and policy impacts of COVID-19 with the Labour Force Survey (LFS) and a household income generation model (IGM) (Sologon, Van Kerm, Li and O'Donoghue 2018) to predict the distributional impact and the fiscal costs of the COVID-19.

This study focuses on Ireland as a case study. Ireland was one of the countries that experienced the largest impact of the 2008 financial crisis and one of the highest return bounces. The COVID-19 crisis is thus an additional test of the country's resilience. Moreover, the State has introduced a range of innovative measures including a new social protection system targeting those who became sick, were made unemployed or targeting those who remained in precarious employment. Measures comprised both public sector delivery mechanisms such as new subsidies, but also measures delivered through the private sector such as pauses inmortgage repayments and breaks in child care payments.

2. Methodology

In this paper we attempt to model the distributional impact of COVID-19 and the policy measures introduced to flatten the curve and to mitigate some of the economic impacts of the crisis. These impacts are highly asymmetric, affecting people in different ways and in different dimensions. From an economic perspective, the COVID-19 virus have a number of effects, including:

- Those who get sick have a spectrum of consequences from self-isolation and time away from work, study and family to hospitalization and mortality.
- A far greater proportion of the population are affected by closing businesses and their loss of income or the social implications of cocooning. Unlike a typical demand shock,

the biggest impacts are felt by those in so called non-essential businesses. The income implications are varied from total loss of income to increased income in some retail businesses.

- This impact on the economy has seen a large fall in capital asset values.
- Various policy responses such as the Pandemic Unemployment Payment or the Temporary Wage Subsidy will have mitigated some of the impact of job loss or wage reduction, but not fully.
- Agreements with banks in relation to mortgages, a freeze on evictions and supports for child care providers will improve the cash flow of households.
- However some households who have not lost their income will indirectly have received a windfall gain in terms of an increase in purchasing power during the crisis as a result of lower work related costs or higher benefits than work income.

Ideally in undertaking an analysis of these effects , we would use household survey data to assess distributional impacts. However there is a time lag between collection and release for research and analysis. For example, the main survey used that contains the income situation of households is the Survey of Income and Living Conditions. The most recent analysis undertaken is for 2018. In normal times a lot happens in a two year period, but in a crisis the changes are so significant that such a lag can mean the data is relatively meaningless.

There are more recent datasets available that can assist such as the Labour Force Survey, which is available on a quarterly basis at a six week lag or the Live Register data and Price data that's available on a monthly basis on a short lag. However these datasets do not contain income information. Understanding the characteristics of households including real-time estimates of their incomes enables policies to be targeted to mitigate the impacts of the crisis at least cost.

Nowcasting

Therefore from a methodological point of view there is the key challenge is the lack of up to date information. We propose to overcome this data gap by using a "nowcasting" methodology (O'Donoghue and Loughrey, 2014) with recent data on employment and prices etc to calibrate a microsimulation model of household incomes, taxes and benefits to produce a real time picture of the population and who is affected differentially; (O'Donoghue, 2014; Atkinson et al, 2002).

Existing methods are relatively crude, applying price inflation factors and changing proportionally the employment rate in specific industries and then using a tax-benefit model to explain the policy consequences (Navicke et al., 2013).

We utilise a more nuanced approach which to explain the heterogeneity of changes in the population, by estimating a system of equations that model the income generating process utilising a dynamic modelling approach to update the data (Li and O'Donoghue, 2014; Bourguignon et al., 2001). We use the generic household income-generation model (IGM) developed by Sologon et al. (2018) to compare the drivers of inequality in Ireland and the UK. The IGM simulates the labour market and household market income distribution as a function of personal and household attributes and generates counterfactual distributions under alternative scenarios. Taxes and benefits are simulated using the NUI Galway microsimulation model developed for studying the impacts of an economic crisis (O'Donoghue et al, 2018).

This methodology for historical analysis (Sologon et al., forthcoming). In this paper extend this methodology to simulate counter factual real-time income distributions as a function of more timely Live Register, Price and LFS data to predict the distributional impact of the COVID.

We adapt the framework developed in O'Donoghue and Sologon, (2020) to undertake the COVID impact assessment. Fundamentally this involves the simulation of the core welfare variable of interest and its components. In most microsimulation analyses, disposable income is the main welfare variable. However given the nature of the shock, and the multi-faceted impact on household living standards, it is necessary to utilise an augmented version of disposable income (*).

Disposable income, $Y_{D,t}$, at time t depends upon market income $Y_{M,t}$, benefits $B\left(Y_{M,t}, Z_t, \theta_t^B\right)$ and taxation $T(Y_{M,t}, Z_t, \theta_t^T)$, which are in turn dependent upon personal skills, family characteristics, Z and tax-benefit parameters θ. However, in this analysis, we adjust disposable income for

- work-related expenditures C_t:
- housing costs H_t:
- capital losses Q_t

$$Y_{D,t} = Y_{M,t} - T\left(Y_{M,t}, Z_t, \theta_t^T\right) + B\left(Y_{M,t}, Z_t, \theta_t^B\right) - H_t - Q_t - C_t.$$

To some extent this turns the clock back to microsimulation analyses from the 1980's where disposable income net of housing costs were used occasionally (Atkinson et al., 1993; Atkinson, 1995).

The nowcasting processes involves a number of components, where the methodology is described in O'Donoghue and Sologon (2020)

- Estimation and simulation of a system of hierarchically structured, multiple equations , known as an income generation model that describe the presence $\left(I_{i,t}\right)$ and level $\left(Y_{i,t}\right)$of market incomes (Sologon et al. 2018)
$$Y_{M,t} = \sum_{i=1\ldots m} Y_{i,t}^{*} = \sum_{i=1\ldots m} \left\{Y_{i,t}\left(Z_{i,t}^{Y}, \theta_{i,t}^{Y}, \varepsilon_{i,t}^{Y}\right) \times I_{i,t}\left(Z_{i,t}^{I}, \theta_{i,t}^{I}, \varepsilon_{i,t}^{I}\right)\right\}$$
- A tax-benefit model, described in O'Donoghue et al. (2013), to simulate tax-benefit changes T(), B()
- Income indexation – the change in the level of income resulting from changes to average wages $Y_{i,t}()$

In periods of significant volatility, reweighting may not be appropriate as it may rely excessively on small groups (Klevmarken, 1997). In this case, it may be more appropriate to utilise a dynamic-type income generation model approach to update the data (see Li and O'Donoghue, 2014; Bourguignon et al., 2001).

Due to the large and rapid changes in the structure of the economy during the COVID-19 crisis, we choose to utilise a dynamic ageing mechanism to adjust our income distribution data to account for macro-economic changes. The mechanism has at its core a generic household income-generation model (IGM) similar to Sologon et al. (2018).

The labour market module estimates the statistical distribution of labour market factors: the probability to be at work, to earn income from salaried employment or self-employment, the occupational, sector and industry, choices, the probability of being unemployed, retired (if not working), the prevalence of income sources (investment income, property income, private pension, other income), the probability of paying for housing (home owner, mortgage, rent), the probability of paying contributions (private pensions), the probability of having child care.

The market composition module involves two estimation techniques: (i) binary models for binary outcomes, and (ii) multinomial models for m outcomes, $m > 2$. In order to use the estimated probabilities from logistic models within a Monte Carlo simulation, we draw a set of random numbers such that we predict the actual dependent variable in the base year (see Sologon et al. 2018 and XX, 2020 for the method). The disturbance terms are normally distributed, recovered directly from the data for those with observed incomes, or generated stochastically for those without a specific income source in the data.

At each step, we retrieve the parameters estimates and the individual specific errors for each estimated model, to be subsequently used in simulating counterfactuals. We use the IGM to simulate the impact of changing economic conditions over time. Bourguignon et al. (2002) and Sologon et al. (2019a, 2019b, 2020a) used a similar methodology to disentangle the impact of macro-economic changes on inequality by generating counterfactual distribution - transformations of the income generation process by 'swapping coefficients' between years for the various transformations The simulations involve calibrating econometrically estimated equations in the income generation model to external control totals made available in more timely data than the estimation data, which is made available at lag. The calibration mechanism or alignment is drawn from the dynamic microsimulation literature and described in O'Donoghue and Sologon, (2020).

Projections are based upon a set of external calibration control totals that are available for more recent time periods than the micro income survey data and that reflect the changes in the macro-economic climate in Ireland over the period of the outbreak, particularly in relation to the structure of the labour market. To do this, we draw upon the dynamic microsimulation literature, using an alignment or calibration technique described in Li and O'Donoghue (2014). The objective of calibrating a microsimulation model is to ensure that the simulated output matches exogenous totals (Baekgaard, 2002). In our model we utilise three types of alignment for binary discrete data, discrete data with more than two choices and continuous data, as discussed at length in O'Donoghue and Sologon (2020). In short, we build up our microdata to the present and we calibrate the IGM data to external control totals reflected in the macro trends. This will assure that the IGM is describing the targeted period.

We then use the infrastructure by introducing various shocks (e.g. factoring sector specific impacts, differentiated by age, macro changes, fiscal responses) and create counterfactual distributions and costs under alternative scenarios.

For those with capital income, we assign the probability of holding shares across the age-income distribution on the basis of Monte Carlo estimates using Iterative Proportional Fitting (IPF) and we simulate an average change in the capital value or capital loss at the median (Wong, 1992).

In terms of work -related expenditures, we model and simulate commuting costs and childcare costs. For commuting costs, we first estimate the probability of commuting by car or by public transport as a function of occupation, industry, education, location, and age group (see Table A1 in Appendix A). Second, estimating models for both public transport and motor fuels as a function of household characteristics, disposable income, social group and number of workers, we predicted the proportional increase in these costs as a result of the number of workers in a household relative to not working. Without modelling the commuting distance as a function of income, which may have either a positive or a negative relationship, we assume a flat commuting costs across households, adjusted for the age.

The distribution of childcare costs per week by family type and disposable income decile is approximated using IPF. These averages are, in turn, used to calibrate the simulations based on the estimated models for having childcare and level of childcare expenditure (integrated in IGM).

The simulations involve two steps.

- First, we nowcast survey data to December 2019 (assuming no COVID-19 crisis): $D(W_{t+1})$.
- Second, we assess the impact of COVID on the base 2020 income distribution by comparing the counterfactual distribution $D^*(W_{t+1}(L^*))$ under alternative shock scenarios to the "original" nowcasted distribution:
$$D(W_{t+1}) - D^*(W_{t+1}(L^*)).$$

3. Data and simulation assumptions

Data

In order to apply the dynamic ageing methodology, there is a need for two types of data:

- micro data, on which to perform estimations and simulations, and
- calibration data to align micro data with the recent changes in labour market and income growth.

As the main micro data source we use the 2017 version of the Survey on Income and Living Conditions (SILC). The SILC is a dataset that has been collected in Ireland since 2003 and which is used to form the Irish component of the European Union Statistics on Income and Living Conditions (EU-SILC). It collects information on incomes, labour market characteristics, demographics, and living conditions, which is widely used to undertake analyses on poverty, inequality, and deprivation. The Irish component relies partially on survey and partially on register data. Around 80% of respondents allowed their national social security number to be used to assess administrative data in relation to their benefit entitlement (Callan et al., 2010). A national weighting methodology is utilised to achieve representativeness of the data set with respect to gender, age, region, and household composition.

The main advantage of the SILC data for our analysis is that it has the appropriate variables required for tax-benefit modelling. There are, however, a number of challenges to utilising the EU-SILC for microsimulation modelling, such as time mismatch in the measurement of income and personal characteristics, lack of information on some income components (e.g. wealth or property values) or tax-deductible expenditures (e.g. medical insurance), difficulties with attribution of some income variables to the appropriate unit of analysis (capital income, rental income, private transfers are recorded at the household level although they are often received by individuals), and aggregation of benefits. All these limitations are discussed in detail in O'Donoghue et al. (2013), whose strategy to address them we also follow in this paper.

Calibration data

Underpinning our analysis is a set of calibration control totals reflecting the changes in the macro-economic climate in Ireland over the period, which elapsed between 2017 and the current COVID-19 crisis. In order to account for these changes, we adjust the SILC data using control total for the current employment situation, provision of pandemic wage subsidy, requests for mortgage deferral, shifts in work-related expenditures, and changes in the stock market. This information is drawn from the Live-Register data and official statistics provided by the Irish Central Statistics Office.

Employment Rate and Sectoral Impact

Individuals who lose their job as a result of the COVID-19 crisis are eligible for a COVID-19 Pandemic Unemployment Payment if they lose their job or the COVID Enhanced Illness Benefit if they fall sick. These instruments provide a payment of €350 per week, available to workers who have lost respectively their job on (or after) March 13 due to the COVID-19 (Coronavirus) pandemic or who have fallen sick. They will be in place for the duration of the crisis.

The numbers and type of individuals eligible for payment and directly affected by the crisis are simulated using the income generation model. The overall employment rate is first used to calibrate the income generation model. This is characterised by the number of people in work relative to the population of a particular age group. The Labour Force Survey (LFS) and previously collects data on this. However as a quarterly survey, even with a relatively quick turn-around time from collection to publication, there is typically a 2-3 month lag between data collection and publication. In real time modelling within a period of economic volatility such as the COVID-19 crisis, data that is closer to the period of the crisis is required.

The most suitable data to perform such calculations is the Live-Register Data that is available on a monthly basis, typically 2-3 days after the end of the month, together with weekly updates in relation to aggregates that have been made. As is well documented, Live-Register data does not capture the level of unemployment equivalent to ILO measures. People can be working part-time whilst in receipt of benefits and conversely, someone can be out of work and seeking work, but not eligible for unemployment benefits. However as an indicator in the short term, of a change in economic circumstances, the changes observed in the live register are an approximate indicator of changes in the numbers out of work (or non-employment rate). In this paper, the LFS is used to now cast to December 2019, with the Live Register used to now cast to April 2020.

Taking the change in the numbers in receipt of the pandemic unemployment benefit at the end of March 2020, we model the change in the numbers in employment rate for April 2020 by subtracting the numbers who receive the PUP and CEIB plus additional people in receipt of regular unemployment benefits from the February 2020 employment level.

The impact of the crisis is not a general demand shock, but a highly asymmetric change in employment, with “essential” industries remaining at work and some sectors such as the public sector remaining on full pay, while other industries are experiencing almost a full shut down over the period of the virus. There is relatively limited data in real time as to the sectoral impact of the crisis. As an approximation of initial impact of the crisis, we utilise the same assumptions as McQuinn (2020) did in their macro analysis of potential scenarios of the COVID-19 crisis. Their assumptions assumed no expenditure in entertainment, textiles, the purchase of durables and eating out and radically reduced expenditures in transportation, with increased expenditures in eating at home. Table 1 reports the impact of these assumptions on employment by sector, indicating a reduction of 533000 in overall employment by April 12th 2020.

Although the private sector shrank significantly, parts of the public sector have grown in order to deal with the crisis, particularly in the health sector. In March 2020, public expenditure increased by €959m. Assuming that €232m relates to growth in social welfare expenditure and €364m relating to growth in health expenditures, we assume a growth in the public sector pay bill of €364m. With an output of €116000 per worker in public administration and of €80000 in the social and health sector, this paybill increase would see a growth of 44698 workers. Assuming that the residual workers out of work are in the construction sector, which had just been told to stay at home, Table 1 outlines the assumed change in employment by sector, consistent with the overall change in live-register numbers as a result of COVID-19. Applying age specific changes identified in the Live Register and expressed as a proportion of the population in the SILC.

Table 1. Impact of private sector consumption changes on employment

	Pre-crisis	April 12th	Change
Agriculture, forestry and fishing	87387	86835	-552
Manufacturing industries, mining, quarrying and turf production, electricity, gas and water supply	245052	121216	-123836
Construction	144840	98604	-46236
Commerce	829916	520946	-308970
Transport Storage Communications	94782	84230	-10552
Other	85895	42489	-43406
Sub-Total in receipt of PUP			-533000
Public administration and defence	114711	125323	+10612
Education, health and social work	465123	499209	+34086
Sub-Total of Public Sector expansion			
Total	2067706	1578852	-488854

Note: Employment is expressed in number of individuals.

COVID-19 Cases

Those who get sick as a result of COVID-19 are eligible, if they are of working age for a COVID enhanced Illness Benefit. The enhanced benefit is paid at the enhanced rate of €350 per week where a worker is told to self-isolate by a doctor or the Health Service Executive (HSE) due to being a possible source of infection or has been diagnosed with COVID-19.

Both workers and non-workers are get sick as a result of COVID-19. Table 3 outlines our random allocation of cases across in-work and out of work, within the national age distribution of the COVID-19 cases. Dividing by the proportion of workers in each age group, we derive the recipient rate of COVID-19 related illness benefit. The numbers at this stage in the crisis are relatively small however.

Table 2. Distribution of COVID-19 cases by age group by work status

	Age Group								
	0	1-4	5-14	15-24	25-34	35-44	45-54	55-64	65+
In-work by Age	0	0	0	91	413	452	441	259	61

Out-of-Work by Age	9	12	33	164	265	299	323	325	857
Pandemic Benefit Rate	0.0000	0.0000	0.0000	0.0008	0.0042	0.0035	0.0037	0.0022	0.0011
Illness Benefit	0	0	0	1443	6574	7196	7007	4116	964

Source: COVID-19 Dashboard (https://geohive.maps.arcgis.com/apps/opsdashboard/index.html#/29dc1fec79164c179d18d8e53df82e96), accessed April 6th 2020.

Mortgage Interest

The State agreed with the main Irish banks that they would allow freezing of up to three months on loan and mortgage repayments for customers financially impacted by Covid-19. As of March 28th, 28000 applications had been made to defer mortgage payments, with approximately a further 7000 being approved per day. This resulted in a total of 45000 mortgage deferrals by April 12th (Table 3).

Table 3. Number of requests for mortgage deferral

Number of Requests as of March 28	28000
Per Day	7000
Number of Requests as of April 12	45000

Source: https://www.rte.ie/news/business/2020/0328/1127000-banking-mortgages-coronavirus/ https://www.irishexaminer.com/breakingnews/ireland/mortgage-breaks-for-six-months-as-45000-apply-for-payment-pause-993714.html

Work Related Expenditures

When people are working at home during the COVID crisis, a number of work related expenses will not be incurred. These include expenses such as commuting costs and child care costs.

In order to work out commuting costs, the Household Budget Survey from 2016 was used. The average modelled total commuting cost per week constitutes €9.17 for one worker, €14.42 for two workers and €23.82 for three workers (Table 5). It should be noted that those who do not work also have transport costs for other purposes. While the actual cost of commuting for work may be higher, it is assumed that there would be some substitution if an individual was not working.

Table 4. Cost of commuting per week

	Number of Workers		
	1	2	3
Proportional Increase in Cost relative to not working			
Motor Fuels	0.263	0.482	0.721
Public Transport	0.172	0.253	0.595
Cost per week			
Motor Fuels	7.41	13.59	20.33
Public Transport	1.76	0.83	3.49
Total per week (€)	9.17	14.42	23.82

Source: Household Budget Survey 2015-16

The State announced measures to support Childcare Providers and Parents during COVID-19 closures, to provide sustainability to the childcare sector and ensure that parents do not have to pay childcare fees during this COVID-19 crisis, while providing them with reassurance that they will maintain their childcare places.[3] The Household Budget Survey reports the both the distribution of child care costs per family type and by disposable income distribution. Utilising IPF a table of the distribution of child care costs per week by family type and disposable income decile is reported in Table 5. These averages are simulated across households in the sample on the basis of the regressions outlined in Table B.1 in Appendix B.

Table 5. Distribution of Child Care Costs per Week by Family Type and Disposable Income Decile

Family Type	1	2	3	4	5	6	7	8	9	10	Total
1 adult with children	2.9	7.8	3.3	22.0	22.4	39.1	68.0	65.9	191.2	268.5	18.1
2 adults with 1-3 children	1.9	5.1	2.2	14.5	14.7	25.8	44.8	43.4	126.1	177.0	49.9
Other households with children	0.7	2.0	0.8	5.6	5.7	9.9	17.2	16.7	48.4	68.0	15.2
Total	0.4	1.0	0.6	5.5	4.7	7.6	12.9	13.6	30.2	40.3	12.0

Source: Household Budget Survey 2015-16

It is assumed that those who are in receipt of Pandemic Payments or those who are non-essential workers, working from home, do not incur commuting costs or child care expenses in the simulation.

Pandemic Wage Subsidy

In order to incentivise employers to retain their work force during the COVID crisis, the state introduced a COVID-19 Temporary Wage Subsidy Scheme on the 24th of March 2020. It aims to keep employees registered with their employers, so that they will be able to get back to work quickly after the pandemic. Businesses with a minimum of 25% decline in turnover between 14 March 2020 and 30 June 2020 are eligible for the scheme. The scheme was initially based upon 70% of an employee's net earnings (after income tax, PRSI and USC) and is paid up to a maximum ceiling of €410 per week. The payment is limited depending on the employee's average take home pay:

- Average pay from €0 to €586 limits it to €410
- Average pay from €586 to €960 limits it to €350
- Average pay above €960 is not entitled to the subsidy.

On April 15th, changes were announced to the temporary wage subsidy.

- The subsidy will increase from 70% to 85% for employees with a previous average take home pay below €412 per week
- The subsidy will be €350 per week for employees with a previous average take home pay between €412 and €500 per week
- The subsidy remains the same for employees with a previous average take home pay of between €500 and €586 per week
- A tiered system has been introduced for employees with a previous average take home pay of over €586 per week
- Employees who were taking home more than €960 per week will be able to avail of the scheme, with tapers depending upon the proportion paid by the employer

As of April 9th , 219400 people had applied for the scheme, allocated across sectors based upon Irish Revenue Commissioner Data.

3 https://www.gov.ie/en/press-release/e37415-minister-katherine-zappone-announces-measures-to-support-childcare-p/

Table 6. Temporary wage subsidy participation rate on April 9th 2020

	#Wage Subsidies	Work PostPUP	Subsidy Rate
Agriculture, forestry and fishing	2411	77332	0.031
Manufacturing industries, mining, quarrying and turf production, electricity, gas and water supply	35726	113967	0.313
Construction	28494	91348	0.312
Commerce	110248	502114	0.220
Transport Storage Communications	12932	83396	0.155
Public administration and defence	658	110314	0.006
Education, health and social work	21480	449251	0.048
Other	7452	38587	0.193

The Wage Subsidy will have a relatively minimal distributional impact as the state subsidises the payments received by employees from employers. It does however shift the balance between private sector and public sector expenditure. More details on the calculation of this Wage Subsidy is provided in Appendix C.

This subsidy does not however take into account the impact of wage reductions where employers did not have the cash flow to make these payments as in the case of individuals whose take-whom pay exceeds the wage subsidy limit. Prior to the introduction of the subsidy scheme there had been pay reductions for staff in certain sectors most affected by the crisis, where staff were not made redundant, such as the airline sector. For example the two main airlines (Ryanair and Aer Lingus) halved the pay of staff when flights were grounded.[4]

Stock Market

The onset of the COVID-19 crisis saw a large fall in stock markets across the world. The Irish index, ISEQ fell by 32% from January 1 to April 1 2020. The holding of shares is quite variable across both the income distribution and the age distribution. Table 7 reports an analysis of the Irish Household Finance and Consumption Survey in 2018. The top 20% of incomes are 8 times more likely to hold shares than the bottom 20% of households. In addition, the value of financial assets for those who hold shares is 9 times higher. However, those in the 20-39 quintile have a relatively high average value for those who hold shares, perhaps related to age. The distribution of financial assets across the age distribution is not as extreme, with those aged 40-79 more likely than other age groups to hold shares. The average value of shares held per household varies with age, but is not monotonic.

[4] https://www.irishtimes.com/business/work/coronavirus-employers-should-seek-consent-for-pay-cuts-lawyer-1.4221405

Table 7. Distribution of holding and value of shares 2018

Percentile of household income	Less than 20	20-39	40-59	60-79	80-100
Participation in total financial assets (%)	3.3	3	8.3	11.3	24.8
Median values of financial assets (€Thousand)	1.4	8.8	3.1	4.4	12.2
Distribution of total financial assets (%)	1.4	4.3	11	12.5	12.4

Age group	Under 35 years	35 - 44 years	45 - 54 years	55 - 64 years	65 years and over
Participation in total financial assets (%)	5.4	8.7	13.3	13.8	8.3
Median values of financial assets (€Thousand)	14.1	8.4	4	10	12.9
Distribution of total financial assets (%)	4.6	15.3	11.9	5.4	15.5

Source: Household Finance and Consumption Survey

The data equivalent to Table 8, with change in share values by age and income group, was not available during the analysis of this paper. In order to utilise this information in a microsimulation model, Iterative Proportional Fitting (IPF) was used to create an approximation of the share value holdings across the age- income distribution. The average share holding and the median value of holdings were generated separately and then multiplied to get the average value per person in the cell (see Appendix D). Applying the ISEQ index to January 1 2020 and then to April 1, 2020, Table 8 models the net change in the value of shares across the age-income distribution. The Table shows that the biggest losses were experienced by those with the highest incomes and the oldest.

Table 8. Change in shareholdings across the age-income distribution, January 1 – April 1, 2020 (€000)

Age group	Percentile in the income distribution					
	Less than 20	20-39	40-59	60-79	80-100	Total
30	0.000	-0.004	-0.003	-0.006	-0.011	-0.005
40	-0.002	-0.036	-0.032	-0.063	-0.117	-0.055
50	-0.003	-0.047	-0.041	-0.082	-0.151	-0.072
60	-0.012	-0.194	-0.168	-0.336	-0.623	-0.246
70	-0.058	-0.902	-0.783	-1.563	-2.901	-0.698
Total	-0.025	-0.248	-0.134	-0.197	-0.328	-0.183

4. Results

Table 9 summarizes the distribution of different types of monthly incomes before and during the crisis calculated per adult equivalent. It should be noted that the deciles used are based upon adjusted disposable income decile, adjusted for work, housing expenses and capital losses. Looking at the change in the size of market income first, one can see that it has decreased across all deciles of the disposable income distribution, although in absolute terms the decline was larger at the top than at the bottom of the distribution. A substantial increase in the size of benefits during the crisis partially compensated the loss of market income to all individuals regardless of their place in the distribution of household disposable income. In absolute terms, however, benefits grew the most for individuals in the upper tail of the income distribution, where they almost doubled in size during the crisis as compared to the period before. The drop in market income was also accompanied by a decrease in taxes paid. Although it happened across all deciles of the disposable income distribution, it was more sizable at the top than at the bottom. In general, neither changes in benefits nor changes in taxes allowed individuals across all deciles but the lowest one to maintain their pre-crisis level of disposable income. The decline in household disposable income was relatively small among the bottom 6 deciles but was quite large (more than 100 Euros) in the upper tail of the disposable income distribution.

A relevant measure to analyse while trying to trace changes in the real standard of living of individuals is disposable income adjusted for housing costs, work related expenditures and capital losses. The COVID-19 crisis has pushed a substantial share of employees to work from home or to take up temporary unemployment, which resulted in a decline in work-related expenses. Some individuals also took up the opportunity to put on hold interest payment on their mortgages, which induced a decline in current housing costs. Taken together, a decline in those two types of expenditures helped individuals in the lower tail of the income distribution to end up with even higher adjusted disposable income adjusted during the crisis than in the pre-crisis period. For households in the upper tail of the income distribution (from the 7^{th} decile onwards), the adjusted disposable income was still lower during the crisis than prior to it, but the difference was somewhat softened due to the cuts in housing and commuting costs.

Table 9. Distributional characteristics of income before and during crisis (€ per month per adult equivalent)

Decile	Before Crisis							During crisis							
	Market income	Gross income	Disposable income	Disposable income*	Benefits	Taxes	Housing and work expenses	Market income	Gross income	Disposable income	Disposable income*	Benefits	Taxes	Housing and work expenses	Capital losses
1	598.1	924.0	787.0	494.3	325.8	-136.9	-292.8	406.1	917.7	787.0	620.2	511.6	-130.6	-166.8	0.0
2	825.1	1349.2	1145.3	937.6	524.1	-203.9	-207.7	606.0	1305.4	1111.0	1004.3	699.4	-194.4	-106.5	-0.2
3	872.0	1575.7	1332.5	1161.9	703.7	-243.1	-170.7	551.7	1498.5	1285.8	1204.0	946.8	-212.7	-81.7	-0.1
4	1135.8	1879.1	1530.9	1340.3	743.4	-348.2	-190.7	862.2	1804.5	1483.9	1378.9	942.3	-320.6	-104.2	-0.8
5	1621.3	2267.3	1854.1	1579.5	645.9	-413.2	-274.6	1236.9	2181.0	1799.2	1678.9	944.0	-381.8	-119.7	-0.6
6	1949.1	2653.9	2136.3	1855.5	704.8	-517.6	-280.8	1442.6	2488.7	2026.2	1899.5	1046.1	-462.5	-125.6	-1.0
7	2541.5	3193.6	2506.9	2161.0	652.0	-686.6	-346.0	1756.5	2847.6	2283.4	2107.8	1091.1	-564.2	-174.6	-1.0
8	3140.6	3807.6	2890.5	2562.5	667.0	-917.2	-328.0	2145.6	3251.8	2545.8	2381.9	1106.2	-705.9	-162.0	-2.0
9	4100.8	4725.4	3476.2	3096.0	624.6	-1249.3	-380.2	3096.0	4209.4	3123.1	2960.2	1113.5	-1086.3	-158.5	-4.4
10	8035.8	8438.9	5187.0	4676.3	403.1	-3251.9	-510.6	6477.0	7256.4	4568.8	4300.1	779.4	-2687.5	-261.1	-7.7
Total	2282.3	2852.9	2133.7	1843.6	570.6	-719.2	-290.1	1702.1	2589.2	1968.3	1824.4	887.0	-620.9	-142.3	-1.6

Note: Disposable income* stands for household equivalized disposable income adjusted for housing, work related expenses and capital losses. Deciles in the first column are defined within the distribution of household equivalized disposable income adjusted for housing, work related expenses and capital losses.

Table 109 summarizes the absolute change in the distributional characteristics of different types of incomes during the crisis as compared to the period before. As discussed above, individuals at each decile of the disposable income distribution experienced a decline in market income during the crisis, but the decline was much higher at the top than at the bottom. The size of benefits increased by 55.5% during the crisis compared to the pre-crisis level but it was not sufficient to keep the size of gross income at the pre-crisis level. The size of taxes decreased by 13.7% during the crisis but even in combination with much higher benefits it was not sufficient to keep disposable income at the pre-crisis level for all households except the poorest ones. As it becomes evident from Table 10, one of the most important instruments to bumper losses in market income was a decline in housing and work-related expenditures, which halved in size during the crisis. Due to a decline in those expenditures (in addition to the increased benefits and decreased taxes), individuals up to the 70^{th} percentile of the disposable income distribution were even better off financially during the crisis than in the pre-crisis period.

Table 10. Change in distributional characteristics of income before and during crisis (€ per month per adult equivalent)

Decile	Market income	Gross income	Disposable income	Disposable income*	Benefits	Taxes	Housing and work expenses	Share losses
1	-192.0	-6.3	0.0	125.9	185.7	6.3	125.9	0.0
2	-219.1	-43.8	-34.3	66.7	175.3	9.5	101.2	-0.2
3	-320.3	-77.1	-46.8	42.1	243.1	30.4	88.9	-0.1
4	-273.6	-74.6	-47.0	38.7	199.0	27.6	86.4	-0.8
5	-384.4	-86.3	-54.9	99.4	298.1	31.4	154.9	-0.6
6	-506.5	-165.2	-110.1	44.0	341.4	55.1	155.2	-1.0
7	-785.1	-346.0	-223.5	-53.2	439.1	122.4	171.4	-1.0
8	-995.0	-555.9	-344.6	-180.7	439.1	211.2	166.0	-2.0
9	-1004.8	-516.0	-353.1	-135.8	488.8	162.9	221.7	-4.4
10	-1558.8	-1182.5	-618.1	-376.3	376.3	564.4	249.5	-7.7
Total	-580.2	-263.7	-165.4	-19.2	316.5	98.3	147.8	-1.6
% change	-25.4	-9.2	-7.8	-1.0	55.5	-13.7	-51.0	-

Note: Disposable income* stands for household equivalized disposable income adjusted for housing, work related expenses and capital losses. Deciles in the first column are defined within the distribution of household equivalized disposable income adjusted for housing, work related expenses and capital losses. The last line shows the percentage change in each type of income during the crisis compared to the pre-crisis level.

Table 9 and Table 10 suggest that household equivalized disposable incomes were somewhat cushioned during the crisis, which held them from the same decline as we observe in market incomes. This cushioning occurred via a mix of private and public measures, which deviated from the standard social insurance-income maintenance mechanisms. Under private measures, we consider work-related (childcare expenses, commuting costs) and housing (mortgage interests and rent payments) costs, which individuals have to pay from their disposable income every month. Under public measures, we consider new types of benefits and wage subsidies, which were introduced during the crisis to soften a decline in market incomes. In what follows, we discuss these private and public measures in terms of their impacts on incomes along the entire distribution of household disposable income adjusted for housing and work-related expenditure.

Table 11 below summarizes distributional characteristics of private income cushioning measures before and after the crisis. Table 11 documents a decrease in all these expenses along the entire distribution of disposable income during the crisis. The decrease is not observed only for rents that did not vary much before and during the crisis. Child-care expenses recorded a relative decrease of 74% to 96% in all deciles. The relative decrease in commuting expenses was more homogenous along the distribution ranging between 82% and 89%. Mortgage interests decreased at various rates across the distribution, larger at the bottom than at the top, ranging between 5% and 40%. The overall contribution of child-care and commuting in disposable income decreased from 1.9% and 3.5% to shares close to 0. Mortgage and rent expenses, as share of disposable income, remained roughly the same.

Table 11. Distributional characteristics of work expenses and housing costs before and during crisis (€ per month per adult equivalent)

	Before crisis				During crisis			
Decile	Child care expenses	Commuting expenses	Mortgage interest	Rent	Child care expenses	Commuting expenses	Mortgage interest	Rent
1	48.2	36.0	27.1	134.3	6.8	4.6	22.0	134.3
2	31.1	45.2	29.7	71.1	4.5	4.7	26.7	71.1
3	23.8	43.0	16.6	62.9	3.7	5.7	9.8	62.9
4	22.8	47.8	23.9	74.1	0.9	5.9	22.6	74.1
5	45.5	69.0	49.4	63.3	2.9	7.9	45.2	63.3
6	37.4	81.2	63.3	61.7	2.0	11.2	52.3	61.7
7	44.4	91.0	84.9	80.6	4.8	15.3	73.5	80.6
8	41.1	103.4	73.9	79.5	5.4	14.9	62.8	79.5
9	52.1	122.2	95.9	36.1	10.6	20.1	87.4	36.1
10	71.5	145.1	137.1	80.9	18.1	25.4	129.8	80.9
Total	41.5	74.1	56.3	77.9	5.9	10.8	49.6	77.9
% of disp. income	1.9	3.5	2.6	3.7	0.3	0.5	2.5	4.0

Note: * Equivalised disposable income after housing costs and work expenses.

Table 12 shows the average weekly work income for each sector of economic activity, as well as the distribution of the receipt of the COVID-related benefits (pandemic unemployment benefits, COVID enhanced illness benefit) and wage subsidies. The highest average weekly work income is recorded in the manufacturing[…] sector, followed by transport[…], whereas the lowest is recorded in constructions and commerce. The prevalence of PUP is the highest in manufacturing[…], commerce and constructions. The wage subsidy is applied in all sectors, with higher rates in public administration, manufacturing […] and agriculture […]. Among the three policy instruments, PUP is used the most, with over a quarter of the work force benefiting from it.

Table 12. Sectoral characteristics of work income and COVID benefit receipt

	Average weekly work income	Proportion with PUP	Proportion with CEIB	Proportion with wage subsidy
Agriculture, forestry and fishing	915.0	0.023	0.007	0.072
Manufacturing industries, mining, quarrying and turf production, electricity, gas and water supply	965.6	0.493	0.015	0.075
Construction	662.2	0.305	0.018	0.062
Commerce	662.8	0.424	0.009	0.040
Transport Storage Communications	769.6	0.103	0.018	0.042
Public administration and defence	814.5	0.000	0.023	0.081
Education, health and social work	803.5	0.000	0.016	0.058
Other	878.3	0.000	0.034	0.053
Total	763.5	0.258	0.014	0.043

Note: PUP: Pandemic Unemployment Payment'; CEIB: COVID Enhanced Illness Benefit

Next, we break the levels of employment, work income, and COVID benefit receipt by the distribution of household disposable income adjusted for work-related and housing costs (Table 13). Employment shares are lower for the bottom than for the top deciles of the income distribution. The most affected in terms of employment rates in the bottom half of the distribution are the 3rd and 4th deciles. This, however, is not reflected in their average weekly work income, which is not the lowest among the bottom deciles. Among the top half deciles, the rank in disposable incomes is positively associated with the average weekly work income, whereas among the bottom half deciles the trend is unclear, most probably due to commuting costs (those with higher commuting costs are at the bottom of the income distribution).

Table 13. Distributional characteristics of work income and COVID benefit receipt (equivalised disposable income after housing costs and work expenses)

Decile	Employment	Average Weekly Work Income	Proportion with PUP	Proportion with CEIB
1	0.365	323.0	0.105	0.003
2	0.335	435.5	0.079	0.007
3	0.299	498.1	0.106	0.002
4	0.300	515.6	0.080	0.003
5	0.441	506.7	0.110	0.012
6	0.458	549.4	0.111	0.003
7	0.512	662.0	0.146	0.009
8	0.560	770.7	0.171	0.005
9	0.636	875.3	0.160	0.013
10	0.733	1558.3	0.131	0.008
Total	0.469	763.5	0.121	0.007

Note: PUP: Pandemic Unemployment Payment'; CEIB: COVID Enhanced Illness Benefit

Table 13 further shows that the highest prevalence of PUP is in the top half of the distribution, with shares higher the higher the rank in disposable income. In total, 12% of the entire population benefited from PUP. Overall, we find a positive relationship between the prevalence of PUP and income deciles. Given our simulation assumptions, as expected, the distribution of CEIB across income deciles follows the age distribution. Overall 0.7% of the population benefited from it.

Table 14 shows how the four COVID mitigation instruments are distributed across deciles of disposable income in absolute levels per adult equivalent. The largest amounts of wage subsidies, PUP and mortgage deferrals are concentrated among the top half deciles. PUP makes up 10.8% of disposable incomes, whereas the wage subsidy contributes 4.1%.

Table 14. Distributional characteristics of COVID mitigation instruments (€ per month per adult equivalent)

Decile	COVID wage subsidy	PUP	CEIB	Mortgage deferral
	58.7	138.0	4.1	5.0
2	62.7	121.8	11.3	3.0
3	68.7	182.8	3.3	6.8
4	46.1	153.1	6.7	1.3
5	73.0	227.0	24.2	4.2
6	119.8	237.9	7.2	10.9
7	115.2	330.0	14.2	11.3
8	105.6	369.6	9.6	11.2
9	159.7	369.3	28.0	8.4
10	93.5	287.6	17.1	7.2
Total	87.0	229.7	11.9	6.7
% of disposable income	4.1	10.8	0.6	0.3

Note: * Equivalised disposable income after housing costs and work expenses

Table 15 summarizes changes in inequality of different types of incomes during the crisis as compared to the pre-crisis period and identifies contributions of benefits, taxes and work-related and housing costs to these changes. The contribution of benefits to redistribution is derived as the difference in the Gini coefficients calculated for gross and market incomes. The contribution of taxes to redistribution is derived as the difference in the Gini coefficients calculated for disposable and gross incomes. The contribution of work-related and housing costs to redistribution is derived as the difference in the Gini coefficients for disposable income adjusted for work-related and housing expenditures and disposable income without these adjustments.

Table 15. Gini coefficient before and during crisis

	Market income	Gross income	Disposable income	Disposable income*
Gini				
Before Crisis	0.499	0.356	0.295	0.323
During crisis	0.578	0.339	0.282	0.293
Change	0.079	-0.017	-0.013	-0.030
Redistribution	Benefits	Taxes	Work-related and housing costs	
Before Crisis	-0.143	-0.061	0.028	
During crisis	-0.239	-0.057	0.011	
Change	-0.096	0.004	-0.017	

Note: Disposable income* stands for household equivalized disposable income adjusted for housing, work related expenses and capital losses.

Table 15 shows that inequality in market income increased by 0.079 points during the crisis as compared to the period before. In contrast, inequality in gross income, disposable income, and especially disposable income adjusted for work-related and housing costs decreased by 0.017, 0.013, and 0.030 points accordingly. Out of three redistributive instruments (i.e. benefits, taxes, and work-related and housing expenditures), changes in benefits contributed the most to the decline in inequality, being followed by changes in work-related and housing costs whereas the redistributive role of taxes slightly decreased during the crisis as compared to the period before.

5. Discussion

Our analysis shows how the combination of crisis-induced income-support policy innovations combined with existing progressive elements of the tax-benefit system were effective in avoiding an increase income inequality in the early stages of the Covid-19 emergency. On a methodological level, our analysis shows how an approach that combines microsimulation and nowcasting can provide real-time information to policy makers on the income distribution implications of economic shocks and policy responses even where the availability of survey data comes with unavoidable lags. Needless to say, the application of this methodology requires that we make a number of assumptions. However, with careful sensitivity analysis, the model provides a flexible tool to policy designers to explore the implications of alternative assumptions in addition to alternative policies.

This approach could be of significant value as we enter the next phase of the crisis response. This phase is likely to involve a gradual reopening of the economy and possibly adjustments to income support policies such as improved targeting or benefit targeting. The methodology is well-designed to explore the relaxation of the shutdown in targeted sectors (which will effect employment rates in those sectors) as well as changes in benefit generosity and subsidy rates. Using the model, policy makers could explore a menu of policy combinations in terms of their impact on key welfare measures and fiscal costs.

To illustrate the application of the model, we have focused in this paper on particular welfare measures, notably the average decile values of various measures of income and the Gini coefficient measure of income inequality for these measures. This analysis can be extended to include other welfare measures – such as various measures of poverty – as well as an explicit consideration of fiscal costs. Policy decisions are likely to depend on multiple outcome measures in designing their policy responses. The modelling approach illustrated in this paper can inform the trade-offs between measures – e.g. attenuating the rise in inequality or poverty while limiting the fiscal costs – that are inherent in the policy-design challenge.

6. Conclusion

The speed with which the crisis has unfolded has required a swift response from policy makers to help families cushion the economic shock. This requires a timely understanding of the scale and direction of recent changes in the income distribution. This, in turn, is hindered by the lack of timely available data. In managing income distribution impacts (and associated fiscal costs) it is valuable to be able to assess the effects of different wage and unemployment support policies given the most up-to-date information on the labour market.

We overcome the lack of data by conducting the first calibrated simulation based upon actual data aiming to assess the distributional implications of the COVID-19 crisis in Ireland using the nowcasting approach developed in O'Donoghue and Sologon (2020). This approach allows us to explain better the heterogeneity of changes in the population by utilizing a dynamic income generation model calibrated using up-to-date information from Live Registers, Price and LFS data, and policy reports.

We extend the standard definition of disposable income by adjusting it for work-related expenditure, housing costs and capital losses. The cushioning of disposable incomes occurred via a mix of private and public measures, which deviates from the standard social insurance-income maintenance mechanisms. There is a sharing of the burden between private savings, reduced expenditures and public support measures. An extended income definition is able to reflect this risk sharing.

Our findings show a decline in market incomes along the distribution of disposable income, which is eight times higher at the top than at the bottom. This decline, however, was largely cushioned by public policy measures aiming to (at least partially) preserve incomes of those who lost the job or got sick. We find that all individuals, regardless of their income position, experienced an increase in benefits during the crisis. The size of benefits was not sufficient to cushion the loss in market incomes, but it helped the poorest 50% to avoid substantial losses in gross incomes. At the same time, there was a decline in taxes paid along the distribution, but, as expected given the drops in market incomes, the decline was more pronounced among the more affluent part of the distribution.

Despite the increase in benefits and decline in taxes, the size of disposable incomes (unadjusted for housing costs and work expenditures) decreased for all individuals, except the poorest ones. Once we account for the decline in housing and work-related expenses, we find that households situated among the bottom 70% of the distribution improved their financial situation, whereas losses are recorded among the top 30%. This indicates that the poorest 70% of the distribution gained under the COVID policy measures (when accounting for the drop in work-related expenditures and housing costs). Despite the fact that the top lost in the crisis, the largest amounts of wage subsidies, PUP and mortgage deferrals were concentrated among the top half of the distribution. The share of PUP's in total disposable income is of 10.8%, whereas wage subsidies contribute 4.1%.

We find that inequality in market income increased during the crisis, whereas inequality in gross and disposable income decreased. Overall, the crisis had an equalizing real-time effect.

References

Atkinson, A. B., Gardiner, K., Lechene, V., & Sutherland, H. (1993). *Comparing Low Incomes in France and the United Kingdom: Evidence from the Household Expenditure Surveys*. University of Cambridge, Microsimulation Unit.

Atkinson, A. B. (1995). *Incomes and the welfare state: essays on Britain and Europe*. Cambridge University Press.

Atkinson, T., Bourguignon, F., O'Donoghue, C., Sutherland, H., & Utili, F. (2002). Microsimulation of social policy in the European Union: Case study of a European minimum pension. *Economica*, *69*(274), 229-243.

Bækgaard, H. (2002). Micro-macro linkage and the alignment of transition processes. *Technical paper*, (25).

Baldwin, R. & Weder di Mauro, B. (Eds.) (2020). *Mitigating the COVID economic crisis: Act fast and do whatever it takes*. London: Centre for Economic Policy Research.

Beirne, K., Doorley, K., Regan, M., Roantree, B., & Tuda, D. (2020). *'The potential costs and distributional effect of COVID-19 related unemployment in Ireland'*. Budget Perspectives 2021 – Paper 1. The Economic and Social Research Institute.

Bourguignon, F., Fournier, M., & Gurgand, M. (2001). Fast development with a stable income distribution: Taiwan, 1979–94. *Review of Income and Wealth*, *47*(2), 139-163.

Bourguignon, F., Ferreira, F. H., & Leite, P. G. (2002). Beyond Oaxaca-Blinder: accounting for differences in household income distributions across countries. Inequality and Economic Development in Brazil, 105.

Callan, T., Keane, C., Walsh, J.R., & Lane, M. (2010). From data to policy analysis: Tax-benefit modelling using SILC 2008. *Journal of the Statistical and Social Inquiry Society of Ireland*, XL.

Gaspar, V. & Mauro, P. (2020). *Fiscal policies to protect people during the coronavirus outbreak*. Blog. International Monetary Fund, 5 March (https://blogs.imf.org/2020/03/05/fiscal-policies-to-protect-people-during-the-coronavirusoutbreak/).

Klevmarken, A. (1997). *Behavioral modeling in microsimulation models: A survey*. Working Paper No 1997: 31. Department of Economics, Uppsala University.

Li, J., & O'Donoghue, C. (2014). Evaluating binary alignment methods in microsimulation models. *Journal of Artificial Societies and Social Simulation*, *17*(1), 15.

McQuinn, K., O'Toole, C., Allen-Coghlan, M., & Coffey, C. (2020). *Quarterly Economic Commentary, Spring 2020*. ESRI Forecasting Series.

Navicke, J., Rastrigina, O., & Sutherland, H. (2014). Nowcasting indicators of poverty risk in the European Union: A microsimulation approach. *Social Indicators Research*, 119, pp. 101-119.

O'Donoghue, C., Loughrey, J., & Morrissey, K. (2013). Using the EU-SILC to model the impact of economic crisis on inequality. *IZA Journal of European Labor Studies*, 2:23, https://izajoels.springeropen.com/articles/10.1186/2193-9012-2-23.

O'Donoghue, C. & Loughrey, J. (2014). Nowcasting in Microsimulation Models: A Methodological Survey. *Journal of Artificial Societies and Social Simulation*, 17(4):12

O'Donoghue, C., Loughrey, J., & Sologon, D. M. (2018). Decomposing the drivers of changes in inequality during the great recession in Ireland using the fields approach. *The Economic and Social Review*, *49*(2, Summer), 173-200.

O'Donoghue, C. and D.M. Sologon (2020). A Microsimulation Based Method to Nowcast Household Income Survey Data. *IZA Discussion Papers.*

Sologon, D.M., Van Kerm, P., Li, J., & O'Donoghue, C. (2018). Accounting for differences in income inequality across countries: Ireland and the United Kingdom. LISER Working Paper No 2018-01.

Sologon D.M., Almeida V., Van Kerm, P & O'Donoghue, C. (2019). Accounting for the distributional effects of the 2007-2008 crisis and the Economic Adjustment Program in Portugal. LISER, 2019, Working Papers

Appendix A Estimation of probabilities of using various types of transport

Table A.1 Probability of using public transport or private transport

	Public Transport			Private Transport | Not Public Transport		
	coef	S.E.	p-vaue	coef	S.E.	p-vaue
Manufacturing industries, mining, quarrying and turf production, electricity, gas and water supply	0.692	0.073	0.000	0.677	0.022	0.000
Construction	0.362	0.076	0.000	1.214	0.024	0.000
Commerce	1.314	0.072	0.000	0.145	0.021	0.000
Transport Storage Communications	2.179	0.072	0.000	0.138	0.021	0.000
Public administration and defence	1.719	0.073	0.000	0.846	0.023	0.000
Education, health and social work	1.167	0.073	0.000	0.532	0.021	0.000
Other	1.424	0.073	0.000	0.043	0.022	0.055
Border Midland and Wester Region	-1.457	0.011	0.000	0.257	0.005	0.000
Occupation 1	0.148	0.013	0.000	0.697	0.008	0.000
Occupation 2	0.098	0.015	0.000	0.412	0.010	0.000
Occupation 3	0.044	0.014	0.002	0.559	0.009	0.000
Occupation 4	0.402	0.012	0.000	0.287	0.007	0.000
Occupation 5	-1.643	0.099	0.000	-1.369	0.023	0.000
Occupation 6	-0.918	0.104	0.000	0.156	0.028	0.000
Occupation 7	-0.342	0.018	0.000	0.926	0.010	0.000
Occupation 8	0.040	0.015	0.009	0.259	0.009	0.000
Aged 20-24	-0.439	0.028	0.000	0.802	0.022	0.000
Aged 25-29	-0.705	0.027	0.000	1.136	0.022	0.000
Aged 30-34	-0.906	0.027	0.000	1.467	0.022	0.000
Aged 35-39	-1.147	0.027	0.000	1.662	0.022	0.000
Aged 40-44	-1.322	0.028	0.000	1.677	0.022	0.000
Aged 45-49	-1.377	0.028	0.000	1.613	0.022	0.000
Aged 50-54	-1.334	0.028	0.000	1.489	0.022	0.000
Aged 55-59	-1.289	0.029	0.000	1.363	0.022	0.000
Aged 60-64	-1.287	0.031	0.000	1.172	0.023	0.000
Aged 65-69	-1.350	0.041	0.000	0.816	0.026	0.000
Aged 70-74	-1.471	0.066	0.000	0.431	0.033	0.000
Aged 75+	-1.606	0.091	0.000	-0.035	0.039	0.360
University Education	0.242	0.007	0.000	0.016	0.005	0.002
Constant	-2.839	0.077	0.000	-0.988	0.030	0.000
Pseudo R2	0.109			0.089		
Number of Obs	1682588			1682588		

Note : Calculated on the basis of Census of Population Data.

Appendix B Simulation of the child care participation and costs

Table B.1. Regression models for having child care (Logit) and level of childcare expenditure

	Coef.	Std. Err.	P>z	Coef.	Std. Err.	P>z
	Has Child Care			Child Care Expenditure		
Number of Children Aged 0 -4	0.833	0.073	0.000	28.0	4.8	0
Number of Children	-0.018	0.057	0.750	0.0	4.0	0.992
Disposable Income (Equivalised)	0.003	0.000	0.000	0.1	0.0	0
Disposable Income (Equivalised) Squared	0.000	0.000	0.000			
Number of Workers = 2 | Lone Parent Working	1.224	0.129	0.000	54.0	9.6	0
Constant	-3.584	0.246	0.000	-15.5	13.1	0.238
R2				0.1437		
Pseudo R2	0.1836					
Observations	1,937			719		

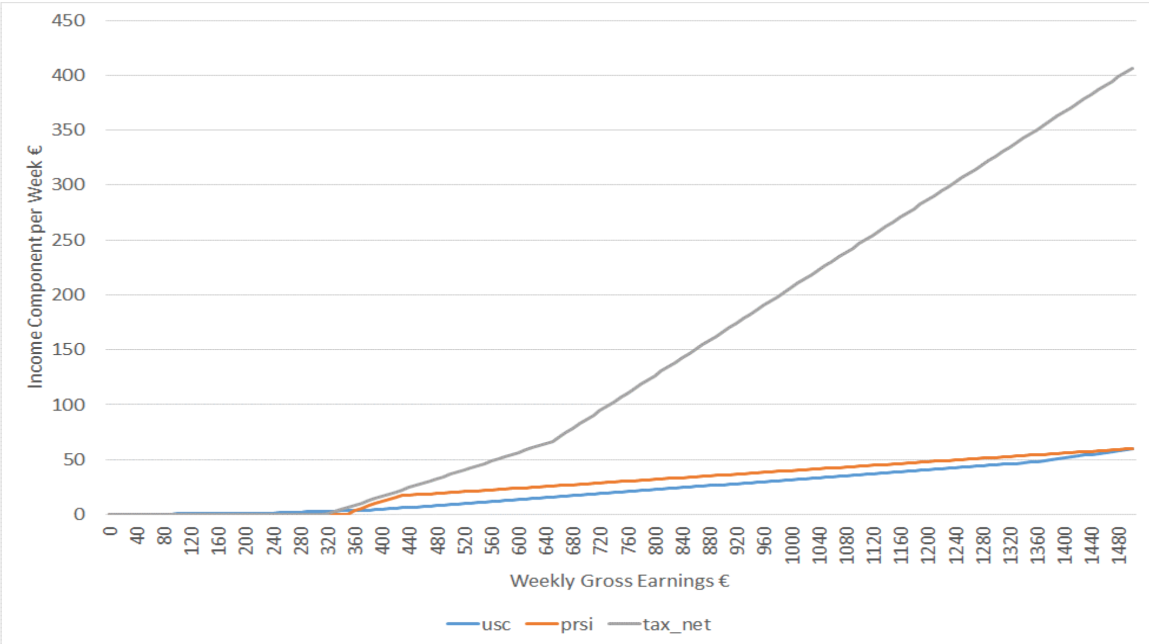
Note : Calculated on the basis of Household Budget Survey 2015-2016.

Appendix C

Functioning of the Pandemic Wage Subsidy

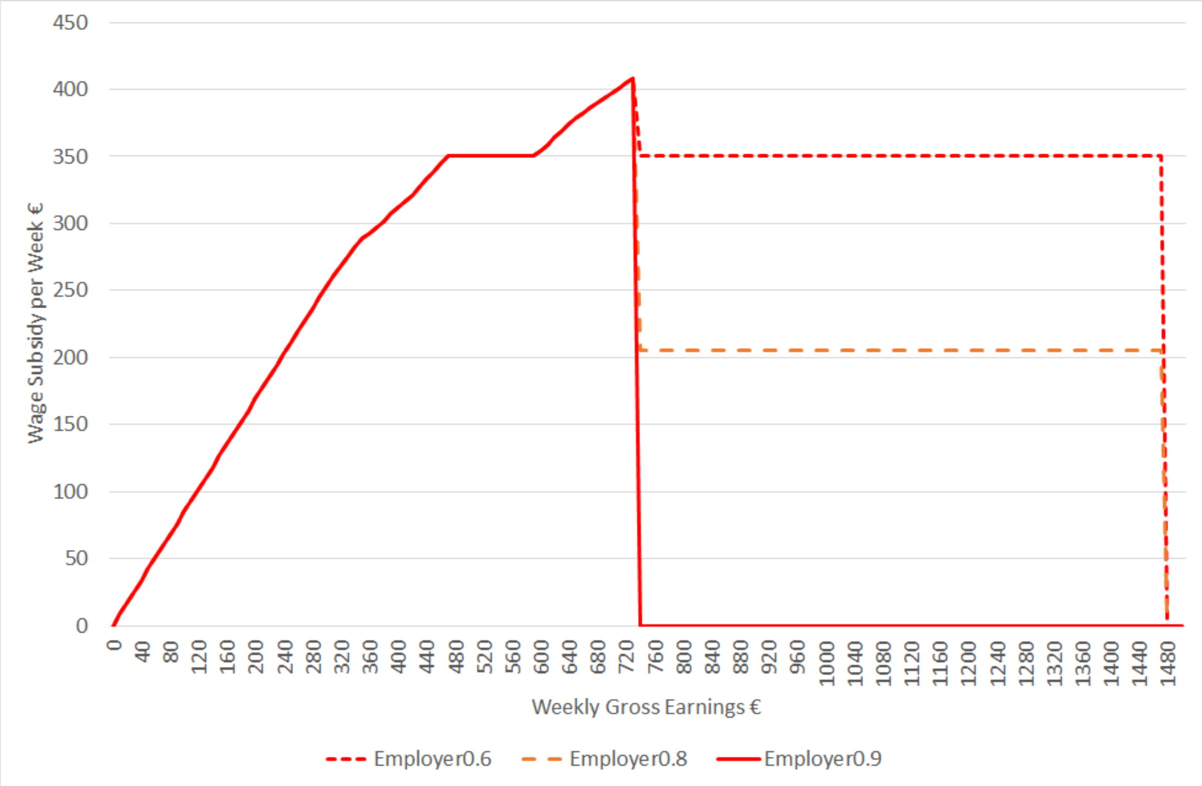
Utilising the 2020 tax schedules in Figures C.1, Figure C.2 describes the functioning of the temporary wage subsidy increasing in proportion to earnings until €586 per week, when a flat rate payment of €350 is made until it is withdrawn completely at net earnings of €960 or gross earnings of €1471. Payments at the higher level, depend differentially on the proportion of subsidy provided by the employer.[5] Although there are a number of kinks in the budget constraint, these are not faced by the employee and given the short term nature of the instrument, it is not assumed to have any adverse effects in terms of bunching.

Figure C.1 Tax calculation for a single person



[5] For further information see, https://www.revenue.ie/en/employing-people/documents/pmod-topics/guidance-on-operation-of-temporary-covid-wage-subsidy-scheme.pdf

Figure C.2 Wage subsidy calculation



Appendix D

Approximation of the share value holdings across the age-income distribution

Table D.1. Age-income distribution of shareholdings proportion, 2018

Age group	Percentile in the income distribution					
	Less than 20	20-39	40-59	60-79	80-100	Total
30	0.012643	0.013099	0.039393	0.056208	0.12114	0.054
40	0.020834	0.021585	0.064915	0.092623	0.199625	0.087
50	0.030946	0.032062	0.096424	0.137582	0.296521	0.133
60	0.037694	0.039053	0.117449	0.167581	0.361176	0.138
70	0.037777	0.039139	0.117707	0.16795	0.36197	0.083
Total	0.029736	0.027031	0.074783	0.101811	0.223442	0.09066

Source: Household Finance and Consumption Survey, with Iterative Proportional Fitting

Table D.2. Age-income distribution of shareholdings €000, 2018

Age group	Percentile in the income distribution					
	Less than 20	20-39	40-59	60-79	80-100	Total
30	0.001	0.010	0.009	0.018	0.033	0.016
40	0.007	0.103	0.090	0.179	0.332	0.156
50	0.009	0.133	0.116	0.231	0.428	0.205
60	0.035	0.548	0.476	0.950	1.763	0.698
70	0.164	2.554	2.217	4.427	8.214	1.976
Total	0.069	0.703	0.379	0.558	0.930	0.518

Source: Household Finance and Consumption Survey, with Iterative Proportional Fitting