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Ireland's Post Crisis Recovery, 2012-2019: Was It Pro-Poor?

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Abstract: This paper examines anonymous and non-anonymous Growth Incidence Curves (GICs) for after-tax disposable income for Ireland during its recovery period after the Great Recession, 2012-19. In the absence of suitable panel data the non-anonymous GICs were constructed on a cohort basis with cohorts formed on the basis of gender, highest level of education attained and the year of that attainment. Both types of GICs are broadly downward sloping over the period indicating that growth was pro-poor on average. Older and less well-educated cohorts fared relatively better over the recovery period, with the corollary that younger, more highly educated cohorts fared relatively less well. Virtually every cohort experienced positive growth however.

Keywords: pro-poor growth, growth incidence curve, cohort analysis.

JEL Codes: I31, I32, O4.

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1. Introduction

Madden (2014) used Growth Incidence Curves (GICs) (Ravallion and Chen, 2003) to analyse the extent to which Ireland's highly volatile growth experience over the period 2003-2011 was "pro-poor". Ireland went from having one of the highest growth rates in the OECD in the period just leading up to the financial crisis of 2008 but then experienced one of the deepest recessions. Most indicators (see the next section for a more detailed discussion) suggest that Ireland "bottomed out" around 2012 and then started a cautious recovery in 2013. By the mid to end part of the decade, this recovery was well-established, although in turn it was to be hit by the economic turmoil associated with the Covid-19 pandemic.[1]

This paper updates the analysis of Madden (2014) to examine the nature of growth in the recovery period, 2012-2019, with one important addition. We first analyse anonymous GICs (as in Madden, 2014) These curves have gained popularity in the literature over recent decades due to their effectiveness at graphically illustrating how the gains of economic growth (or contraction as the case may be) varied across the distribution of income (Ravallion and Chen, 2003). Loosely speaking (we give a formal definition below), if growth between periods t and t+1 is predominantly concentrated amongst lower percentile observations, then it can be described as pro-poor. GICs provide a simple graphical way of checking if this is the case.

Second, this paper also analyses non-anonymous GICs (NAGICs). As will be explained in more detail below, anonymous GICs compare the position of a person at percentile p in period t with that of the person at percentile p in period t+1 (and does this for all percentiles and traces out the curve for all values of p). However, in all probability these will *not* be the same person (unless there is no reranking between periods t and t+1 which is highly unlikely). NAGICs compare the position of the person at percentile p in period t with the position *of*

[1] At time of writing (June 2021) the pandemic is ongoing and clearly it is likely to have a major impact upon personal income growth. For the moment however, SILC data is only available up to 2019 and so we confine our analysis to the 2012-2019 period while acknowledging the possibility of dramatic developments post-2019.

that same person at period t+1, thus allowing for re-ranking, and traces out the relevant curve for all values of p.

The calculation of NAGICs requires the availability of panel data, whereby the same individuals are followed over time. While there is a rotating panel available in EU-SILC (the dataset we use), it is only suitable for construction of individual level NAGICs over a short period of time (typically year-by-year). Our approach, and one of the principal contributions of our paper, is to construct NAGICs on a cohort basis (effectively a pseudo-panel approach) to analyse non-anonymous growth in Ireland over a longer time period. However, the construction of NAGICs on a cohort basis enables us to uncover how the average experience of growth differed by population cohort, as defined by specified population characteristics – namely, gender, highest level of education achieved and *when* that level of education was achieved (in ten year brackets). Including NAGICs in the scope of the analysis provides insight into the 'types' of people that were actually gaining (or losing) as a result of the growth process, and how their respective experiences compared to other cohorts.

The paper proceeds as follows: in the next section we briefly review the growth performance of the Irish economy from a macro perspective over the 2012-2019 period and also review related work in this area. Section 3 explains the construction of GICs and NAGICs. In section 4 we discuss our data and in particular the basis upon which we construct our cohorts to obtain NAGICs on a cohort basis. In section 5 we present our results before some discussion and concluding comments.

2. Ireland's Recovery Period: 2012-2019.

In this section we give a brief overview of macroeconomic developments in Ireland over the 2012-2019 period and we also discuss related work in this area. As explained in a recent paper by Honohan (2021), headline figures such as Gross Domestic Product (GDP) per capita are particularly misleading as a measure of living standards for Ireland. The large fraction of profits repatriated by multinational companies in Ireland has always inserted a wedge between GDP and Gross National Product (GNP). However, as Honohan points out, two additional distortions have developed in the last decade. First of all, many multinationals now "locate" highly valued assets in Ireland (such as intellectual property) and since the depreciation of these assets must be accounted for in any "gross" measure of output such as GDP, GNP or Gross National Income (GNI), this had led to these gross measures being artificially distorted upwards.

In addition, some multinational entities have relocated their headquarters to Ireland and hence their non-distributed profits are counted in Irish output, even though their shareholders are for the most part not Irish residents. The combination of these two factors led to the development of the GNI* measure (which effectively corrects for both of them in addition to the traditional GDP/GNP correction) and which in level terms is about 40 per cent lower than GDP (this contrasts with most countries where they are approximately equal).

Table 1 shows how these aggregates have developed (in terms of per capita growth rates) over the 2012-2019 period. In addition, we also include the growth in private consumption and the level of end-year unemployment, as these also seem reasonable as good indicators of overall living standards of individuals. Our choice of 2012 as initial year is motivated by it being the most plausible year for the bottoming out of the Great Recession and the start of the recovery. It is the first year where unemployment starts to fall and we no longer see the precipitous falls in macroeconomic aggregates which had been witnessed in the immediately preceding years.

Thus, for our analysis of pro-poor growth on both an anonymous and non-anonymous basis, we will examine the overall period from 2012 to 2019. However we also perform sub-period analysis for 2012-2015 and 2015-2019. It seems fair to say that Ireland's recovery can be split into two phases. Initially it consisted of what could be viewed as stabilisation where things simply stopped getting worse, but then in the second part of the period a genuine recovery was observed. We choose 2015 as our pivot year. It is the mid-year for our analysis and by coincidence is also the year when multinationals relocated a large fraction of their intellectual property assets to Ireland leading to a freak rise in GDP/GNP for that year.

Before explaining the GIC methodology, we review related work for Ireland. Much of the applied work covers the Great Recession, with analysis typically beginning around about 2008 and finishing around 2013. Thus the recovery itself, in particular its latter stages, has received less coverage.

Two of the papers most relevant to our study are those of Callan et al (2017) and Savage et al (2019).[2] They examine the impact of the Great Recession and consequent policy responses on inequality in Ireland. They analyse how inequality evolved over the 2008-2013 period

[2] There is considerable overlap in the analysis of both papers so we will discuss them together.

and in particular the contribution of various different factors: the recession itself, automatic fiscal stabilisers and discretionary policy changes. They conclude that market income inequality (essentially income before automatic and discretionary fiscal policy is accounted for) saw a marked rise. However in terms of inequality of after-tax disposable income, this was offset principally by automatic stabilisers, while discretionary fiscal policies overall had a neutral impact. The net impact of these effects is that standard inequality indices for after tax disposable income show remarkable stability over such a tumultuous period.

What is most relevant from our point of view is that these papers construct non-anonymous GICs using the rotating panel data of SILC. As mentioned in the introduction, the rotating element of the panel, whereby owing to rotation and attrition effectively only about 50 percent of the sample is retained from year to year, implies that GICs can only realistically be constructed on a year by year basis. They show that those individuals who started the period in the lower deciles on average experienced higher growth on a year by year basis than those in the middle of the income distribution, who in turn experienced higher growth than those at the top of the distribution. When combined with the finding that overall inequality (as measured by anonymous indices such as the Gini coefficient) showed little change over the period this suggests a reasonable degree of year by year re-ranking. They note that this happens during both boom and recession years. Our analysis in this paper will investigate whether this persists through the recovery period.

Callan et al (2018) also investigated the evolution of inequality in a number of EU countries over the same period using a broadly similar methodology (excepting the GIC analysis). They again find the most important role for automatic stabilisers in offsetting the effect of increased market income inequality during the Great Recession. However, again, their analysis only extends as far as 2013/14 and so does not include the full recovery period.

O Donoghue et al (2018) applied the Fields methodology to decompose changes in inequality in Ireland over the 2007-2012 period. In line with other studies of this period, they find that inequality fell in the early part of the crisis, but then rose again to approximately its pre-crisis level. However such relative stability in inequality can mask countervailing changes in the forces driving inequality, which is the subject of the analysis in their paper. The paper uses a regression-based approach to break down the change in inequality into a component accounted for by a change in individual characteristics (the “quantity” effect) and a component accounted for by a change in the return to characteristics (the “price” effect), similar to the well-known Blinder-Oaxaca decomposition of means. Similar to the results of Savage et al (2019) they find that market income inequality rose, however it was offset by both automatic and discretionary changes in taxes and benefits. In terms of the factors included in the regression, they find that labour market drivers had the largest impact upon inequality with a diminishing role for education. It is also noticeable that in general they find price effects to be greater than quantity effects.

Finally, Roantree et al (2021) provide an overview of inequality in Ireland over the period 1987-2019. They combine a number of different data sources, most notably the Living in Ireland Survey from 1994 to 2001 and EUSILC from 2003 to 2019, but take care to employ a measure of disposable income which is comparable over the different surveys. They show a gradual decline in inequality as measured by familiar indices such as the Gini coefficient and the 90:10 ratio. Perhaps of most relevance to this study they also include anonymous GIC curves for the period as a whole and also for sub-periods. For the period most relevant to our study (2012-2019) their GIC curve is downward sloping over most centiles, though showing a slight uptick over the two highest centiles. We will compare our results to theirs below, bearing in mind that some slight differences should be expected: firstly they use a different equivalence scale to that employed by the CSO and secondly our estimation sample will differ slightly from the CSO full sample (see table A1).[3]

We now explain the derivation of growth incidence curves.

3. Growth Incidence Curves

Growth Incidence Curves (GICs) were first introduced by Ravallion and Chen (2003). Following their notation let $F_t(y)$ be the cumulative distribution function (CDF) of income, giving the proportion of the population with income less than y at date t. Inverting the CDF at the pth quantile gives the income of that quantile. Thus

$$y_t(p) = F_t^{-1}(p) = L_t'(p)\mu_t \text{ with } y_t'(p) > 0$$

where $L_t(p)$ is the Lorenz curve with slope $L_t'(p)$ and μ_t is the mean.

[3] The CSO use weights of 1, 0.66 and 0.33 for first adult, subsequent adults and children under 14 respectively. Roantree et al use scales of 1, 0.5 and 0.3.

Now, comparing two dates t and t-1, the growth rate in income of the pth quantile is $g_t^r(p) = [y_t(p)/y_{t-1}(p)] - 1$, where the "r" superscript refers to a relative GIC. Thus when p varies from zero to one, $g_t^r(p)$ traces out what Ravallion and Chen (2003) term the "growth incidence curve" (GIC). From the expression for $y_t(p)$ above it is clear that the GIC curve can also be expressed as

$$g_t^r(p) = \frac{L_t^{'}(p)}{L_{t-1}^{'}(p)}(\gamma_t + 1) - 1$$

where $\gamma_t = (\mu_t/\mu_{t-1}) - 1$ is the growth rate in mean income.

If $g_t^r(p)$ is a decreasing function of p for all p, then growth rates for poorer quantiles are greater than for richer quantiles and so inequality must be falling between period t and t-1 for all inequality measures satisfying the Pigou-Dalton transfer principle.

It is also possible to examine absolute GICs. In this case $g_t^a(p) = y_t(p) - y_{t-1}(p)$ and we examine the absolute growth for each quantile. If the GIC curve for absolute growth is always downward sloping then absolute inequality will be falling between period t and period t-1.

GICs can also be examined on a non-anonymised basis. Recall that the anonymous relative GIC traces out the relationship $g_t^r(p) = [y_t(p)/y_{t-1}(p)] - 1$. The non-anonymous GIC (NAGIC) traces out the proportional change in income for each percentile, as defined in period *t-1*. Thus it does not show the change (or difference) in income for the (anonymous) pth percentile in period t compared to period *t-1*, but rather shows the change in income between period *t-1* and t as experienced by the pth percentile in period *t-1*. Thus the GIC compares the income of people who were not necessarily in the same rank in period t-1 (they are almost certainly different people) whereas the NAGIC on the other hand uses the initial distribution or ranking as a reference (see Grimm, 2007 and Bourguignon, 2011). Following the notation of Grimm, we can define the relative NAGIC as tracing out the relationship $g_t^r(p(y_{t-1})) = \frac{y_t(p(y_{t-1}))}{y_{t-1}(p(y_{t-1}))} - 1$. And likewise the absolute NAGIC traces out $g_t^a(p(y_{t-1})) = y_t(p(y_{t-1})) - y_{t-1}(p(y_{t-1}))$.

Clearly, the calculation of NAGICs requires the use of longitudinal data, since we must be able to trace the experience of the pth percentile between period *t-1* and t. While there is rotational panel data in our dataset (75% are retained each year), when allowance is made for attrition only about 50% "survive" between each waves of data. This suggests that, at best, calculating

NAGICs using individual data is best done only on a year by year basis. In order to calculate them over a longer period we use a "pseudo-panel" approach and employ cohorts. Of course, this comes at a cost as we move from individual to cohort based analysis. However, we see this approach as complementary to that of Savage et al (2019) and we think it can shed some light on the growth experience over Ireland's recovery period.

Rather than dealing with the same individuals over time (as true panel data does) pseudo-panel data deals with stable cohorts and instead of individual observations, within cohort means are employed. Their use dates back to Deaton (1985) who demonstrated that such cohorts could be constructed from repeated waves of cross-sectional data. The advantage of using such data is that they are typically available for a longer run of years and they also do not suffer from the problems of attrition associated with true panel data. When using repeated cross sectional data it is not possible to follow the same individual over time, but it is possible to follow the same *type* of individual, whereby type means membership of a given cohort. The critical issue is thus the construction of these cohorts. They must be based upon observed characteristics which are stable over time, such as gender, year-of-birth and education level (assuming we restrict our sample to people who are likely to have completed their formal education).

Thus, the individual based model is replaced by a cohort based model and the relative NAGIC traces out $g_{c,t}^{r}\left(p\left(y_{c,t-1}\right)\right)=\frac{\overline{y_{c,t}}(p(y_{c,t-1}))}{\overline{y_{c,t-1}}(p(y_{c,t-1}))}-1$, where $\overline{y_{c,t}}$ refers to average income in cohort c in period t. And likewise the absolute NAGIC traces out $g_{c,t}^{a}(p(y_{c,t-1}))=\overline{y_{c,t}}(p(y_{t-1}))-\overline{y_{c,t-1}}(p(y_{t-1}))$.

We now turn to discuss our data and the dimensions we use to construct our cohorts.

2. Data

Table 1 gives an account of how the main macroeconomic indicators evolved in Ireland over the 2012-2019 period. Following the aftermath of the economic crisis that hit Ireland in 2008, economic growth was initially slow and signs of this recovery are visible in the indicators. The recovery became more pronounced however in the latter years, led largely by relatively high tech businesses in the tradable sector (Fitzgerald, 2014). The data from which we derive the GICs come from consecutive cross-sectional surveys (2012-2019) which are the Irish part of the European Union Survey of Income and Living Conditions (EU-SILC).[4] This survey is the successor to the European Community Household Panel survey. After allowing for missing observations for certain variables, the sample sizes are typically around 12,000 for each year. However our sample size will shrink as we make some adjustments which we now describe.

Firstly, we trim our data of the top and bottom 1%. This is quite common in income distribution analysis and it removes outlying observations which may exert undue influence (e.g. Jenkins and Van Kerm, 2016, and Gottschalk and Moffit, 2009). As we are using highest level of education attained as one of the dimensions in constructing our cohorts, we also exclude all those listed as still being in full time education (the vast majority of these are under the age of 24). This leaves us with what we call our estimating sample and it is about 56 per cent of the original sample. Table 1 in the appendix shows summary statistics for the full and estimating sample for our three years of interest, 2012, 2015 and 2019. The difference between the full and estimating sample reflects the exclusion of younger people in full time education from the estimating sample. The changes in age and principal economic status show a population that is slightly ageing and also the improved macroeconomic conditions. However, since, as we explain in detail below, we define our cohorts on the basis of characteristics which we believe to be time invariant over the 2012-2019 period, this should not affect the cohort analysis.

As our income measure we use equivalised income after social transfers, using the EU definition of income (details of this measure are included in the appendix) and the modified OECD equivalence scale (1.0 for first adult, 0.5 for subsequent adults and 0.3 for children aged less than 14). In table 2 we provide summary statistics for mean equivalised income and for the 25th, 50th and 75th percentiles for our sample years. Equivalised income is presented in 2015 prices. Table 2 shows that equivalised income moved more or less in line with private consumption from table 1, especially bearing in mind that the figures reported in table 2 refer to the *previous* calendar year. Thus for example, equivalised income from SILC 2016 actually refers to income for the calendar year 2015.

The data underlying table 2 can be used to construct anonymous GICs, since for example the median income refers to the median for each year and is highly unlikely to be the same individual. In order to construct NAGICs we need to be able to follow the same individuals

[4] For details of the Irish part of EU-SILC see CSO (2007) and the documentation at http://www.cso.ie/eusilc/default.htm

over time. As we explained above, while this is possible on a year by year basis using SILC, the combination of 75% rotation plus attrition mean that following individuals over longer periods is problematic. Hence we use pseudo panel data via the construction of cohorts which we now explain.

Cohorts should be mutually exclusive and exhaustive so that everyone is a member of one cohort only. Perhaps most importantly, cohorts should be constructed so that cohort fixed effects can be reasonably regarded to be unchanged over time. Thus, as far as data permits, cohorts should be constructed on a stable population and on the basis of a stable criterion. Thus individuals (if we could observe them over time) should not be able to switch cohorts.

We construct our cohorts on the basis of three criteria: gender, highest level of education achieved and *when* that level was achieved (in ten year brackets). The latter criterion is particularly useful as it captures not only age effects but also the fact that owing to the gradual drift upwards in education, the earnings implications of different levels of education will have changed over time. Thus, for example, completing secondary school education in the early 1960s would place an individual at a considerably higher "education rank" than the equivalent achievement in the 2010s. We define three levels of education (did not complete secondary schooling, completed secondary schooling and completed third level education) and we provide summary statistics for our three years of interest in table 3. We also have seven categories for age of achievement of highest level of education, and along with gender this gives us 42 (2x3x7) cohorts.[5]

One slight modification we make to the construction of the cohorts concerns the youngest age/education group. While our data does include people who obtain their highest level of education between 2010 and 2014, we do not include this group in our analysis. The reason is that we believe there is a significant compositional change for this group between 2012 and 2019. By 2019 there are people with third level education in this group who were not included in 2012 (as we do not include those in full time education in our analysis). If we were to include those who obtained their highest education between 2010 and 2014, then the cohorts with third

[5] While data in EUSILC is available on when education was completed in five year brackets, we felt the size of each cohort would be too small, so instead we converted these to ten year brackets, with the exception of the 2005-2014 period as explained in the main text.

level education and who obtained it between 2010 and 2014 would show compositional change between 2012 and 2019 which is undesirable for cohort based analysis. Thus while we use ten year brackets up to 2004, for the final age/education grouping we just use the five year bracket from 2005-2009. As can be seen in Roantree et al (2021), median earnings for the 16-34 year group picked up considerably in 2019 relative to 2018. Our analysis will only capture some of this (the part of this group who attained highest education in the 2005-2009 period), but this is the price that must be paid for minimising the degree of compositional change for our youngest cohort.[6]

Clearly there will be variation across different cohorts for a given year and across the same cohort for different years and this is reflected in table 4. The average size of cohort ranges from 130 in 2019 to 173 in 2015. As a rough rule of thumb, a cohort size of about 100 is considered acceptable (Verbeek and Nijmen, 1992). However, we do see considerable variation within each year, with minimum cohort sizes reaching as low as 12 in 2019. The smallest cohort is females with higher level education who received their highest education before 1955. In general, those cohorts with lowest numbers tend to be mirror images of each other: either young (in the sense of receiving their highest education level in the last ten years) people with minimum education, or older people with higher education. The more heavily populated cohorts are younger (though not the youngest) with higher education, and older people who did not complete secondary school.

4. Results

We now present results, first of all for GICs and then for NAGICs. We present results for the 2012-2019 period in total and also for the sub-periods of 2012-2015 and 2015-2019. Figure 1a shows the anonymous GIC for the period in total, from 2012 to 2019. The slope is downward and quite steep up to about the 10th percentile, suggesting strong growth for the first decile. After that the slope is still downward sloping but much more shallow, indicating that growth for the rest of the distribution was slightly pro-poor. However, just after the 90th percentile we see the GIC tick upwards, and then down again, suggesting that at the very top of the distribution growth was to some degree pro-rich. The confidence intervals here are quite

[6] We are grateful to Barra Roantree for helpful discussion on this point.

wide however, so it would be unwise to read too much into this. The same overall shape of GIC (including the uptick at the very top of the distribution) is also observed in the GICs in Roantree et al (2021), which is as expected, given the relatively minor differences in estimation sample and equivalence scale which they use.

The GICs for the sub-periods reveal an interesting pattern, however. That for the first three recovery years, 2012-2015, shows a similar, though not identical pattern to the overall period. The strong growth for the first decile is replicated. However after that there is a slight downward slope up to about the 25th percentile and after that GIC is quite flat, with no uptick at the end. The GIC for 2015-2019 has marginally less pronounced growth for the first decile. However, after that the GIC has a clear downward slope and then that dramatic uptick (albeit with wide confidence intervals) just after the 90th percentile.

Thus the GICs for the sub-periods reveal that for the early stages of the recovery in relative terms it was the very poorest who fared best, while growth across the rest of the distribution was pretty uniform. Thus, while the GIC is pro-poor, this is very much driven by what happens to the lowest decile. For the latter years of the recovery, the GIC is pro-poor in a more uniform fashion in that the slope of the curve is downward at a fairly constant (although not completely smooth) rate, before ticking up at the very top of the distribution.

We now turn to the NAGICs. We must remember that these are drawn on a cohort basis and so we are not tracking the experience of the same individuals over the period. Rather we are tracking the average experience of people in cohorts defined by their gender, their highest level of education and the year that level of education was achieved. We cannot capture the experience of individuals *within* those cohorts, just the average experience for that cohort bearing in mind that the individuals in each cohort change from wave to wave. However, even though the precise individuals in each cohort change over time, the fact that the cohorts are constructed on time-invariant criteria should ensure that it is the same *type* of person in each cohort.

Figure 2a shows the NAGIC for the complete 2012-2019 period. While the curve is not monotonic, it is broadly downward sloping. Cohorts who were relatively poorer in 2012 did relatively better over the period and there is a noticeable drop in growth for the highest ranked cohorts and also around the 60th percentile.[7] Figures 2b and 2c show the curves for the sub-periods. Similar to the case for the anonymous GICs, most of the pro-poor growth occurs in the 2015-2019 period, although the slope is far from monotonic. For 2012-2015 the curve is quite flat over a considerable range, but then we see falls in income for some of the richest cohorts. The 2015-2019 period sees the poorest cohorts and cohorts around the middle doing best (note however that the reference period here is 2015, not 2012).

One of the advantages of the NAGIC approach with cohort data is that while we cannot identify precise individuals, we can identify the cohorts and hence some of the observable characteristics of those who fared relatively well, and badly, over the period. This information is provided in table 5a-5c. In the rightmost column we show the percentage change in average income for this cohort over the period, with asterisks indicating the usual level of significance. We also shade those cohorts where the average cohort size is less than 100 as these are below the rough rule of thumb indicated by Verbeek and Nijmen (1992). We would not place too much reliability on the point estimate results for these cohorts. Even though our test for the null hypothesis of a significant change over the period does take account of sample size, as pointed out by Gelman and Carlin (2014), with small sample sizes point effects have to be very large in order to be statistically significant and it is likely that that the magnitude of the point effect is exaggerated.

Bearing in mind these caveats, which groups did best over the period as a whole and within the sub-periods? Median income growth over the complete period was about 22 per cent. Leaving aside those with low cohort numbers (which we have shaded for convenience), we can identify three cohorts who saw increases of around 35 per cent.[8] These are females who did not complete secondary education and who left school between 1985-94, males who did not complete secondary education and who left between 1975-84 and females who did complete secondary education and who left in the 1995-2004 period. Overall, we do not see a very high representation of cohorts who completed third level education in the top half of the table.

[7] As can be seen in table 5a, three cohorts had negative growth over the period. The smoothing of the GIC curve masks this however. For details re the smoothing in the DASP package, see Arrar (2012).

[8] Though it is interesting to note that, consistent with the earlier observation re younger cohorts doing well in 2019, it is the youngest, least well-educated cohorts who show the highest proportional increase over the 2012-19 period (in excess of 70 per cent). But we reiterate, bear in mind the very small cell sizes here.

Again, ignoring small cell sizes, four of the five worst performing cohorts over the period had completed third level education. Since we would expect a positive correlation between education and the level of income, this is consistent with the NAGIC curve for the period which is broadly downward sloping, indicating that it was the relatively less well-off who did best in the 2012-19 period.

Turning now to the sub-periods, it is important to bear in mind that about two-thirds of the overall growth between 2012 and 2019 occurred in the second part of this period, between 2015 and 2019. For the first sub-period of 2012 to 2015 median growth was just over 7 per cent. Interestingly we see a greater presence of third level cohorts in the top part of the table for this period, as well as some of the less highly educated cohorts mentioned above who fared well over the period as a whole. Median growth for the 2015-2019 period was around 13 per cent and here we see relatively strong growth for older cohorts who completed education in the 1965-84 period with varying levels of education. Of those who did less well for the latter sub-period, again consistent with the results for the period as a whole, we see a relatively higher presence of third level cohorts, who graduated relatively recently (post 1995).

Thus to the extent that a broad pattern by cohort can be observed, it seems most accurate to say that older and less well educated cohorts fared best over the 2012-2019 period, while those who relatively did worst were the more recently graduated third level cohorts. Bear in mind however two caveats regarding these results: cell sizes in some cases are either below or very close to the rule-of-thumb number of 100 and also there is likely to be lots of variation within cells and this will not be captured by cohort based analysis.

5. Conclusion

This short note has updated work from Madden (2014) and used GICs analysis to investigate patterns of growth over Ireland's recovery period, 2012-2019. Both anonymous and non-anonymous growth, the latter using cohort analysis, are examined. Similar to other analysis in this field we find that anonymous growth was broadly pro-poor for the period as a whole and also for the sub-periods of 2012-2015 and 2015-2019. However, the GIC shows a slight upward slope for very highest percentiles (especially for the latter period), indicating that growth was not unambiguously pro-poor.

The cohort analysis is less clearcut, as in some cases cohort sizes are quite small and so it is difficult to draw reliable conclusions. However, similar to the anonymous GICs, NAGICs are generally downward sloping though far from monotonically so. Again, we conclude that growth is broadly, but far from unambiguously, pro-poor. In terms of which cohorts fared well over the period, again it is unwise to draw very firm conclusions as some cohort sizes are quite small, but indications are that older and relatively less well educated cohorts showed the greatest increase in disposable income over the period and more recent, high educated cohorts fared comparatively worse.

A final observation concerns the extent to which our income measure provides a suitable representation of living standards. Whilst EUSILC provides the most reliable measure of disposable income in Ireland available to us, it does not adjust for housing costs or state-provided services. Levels of mortgage debt were still considerably high over the period under consideration owing to the long-lasting effects of the recent prior recession which hit Ireland in 2008. Furthermore, there were shifts in various forms of social supports provided by the state as the economy recovered over 2012-2019. Examples include changes in the availability of special needs teachers, and changes in the numbers of and accessibility to GP Visit cards. It is important to remember that changes in factors such as these may have had a moderate to significant impact on broader living standards in Ireland, which our income measure fails to capture.

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Table 1: Ireland, Key Economic Indicators, 2011-2018

Year	GNP per cap % Change	GNI* per cap % Change	Consumption per cap % Change	Unemployment Rate (%) – end year s.a.
2011	-5.45	-6.50	-3.63	14.8
2012	-0.27	-1.80	-0.65	14.0
2013	5.44	6.22	-0.29	12.2
2014	8.59	8.37	2.00	10.2
2015	13.08	-0.86	2.61	8.9
2016	5.26	3.60	2.66	7.5
2017	5.10	3.49	1.25	6.2
2018	5.87	5.35	1.41	5.5
2019	2.04	0.37	1.83	4.8

Source: Central Statistics Office.

Table 2: Summary Equivalised Disposable Income (€, 2015 prices)

	Equiv Y (mean)	Equiv Y (p=0.25)	Equiv Y (p=0.50)	Equiv Y (p=0.75)
2012	217.65	132.55	188.30	273.88
2015	231.58	139.70	202.10	291.50
2019	266.72	168.38	233.12	324.77

Source: Central Statistics Office, Survey of Income and Living Conditions (SILC), 2012-2019. Note these are mean and quantiles for estimating sample, using sample weights provided.

Table 3: Categories by Year

	2012	2015	2019
Education Level			
Did not complete secondary	0.39	0.37	0.34
Completed secondary	0.27	0.27	0.26
Completed tertiary	0.34	0.36	0.40
Year Obtained Highest Education			
Pre-1950-1954	0.09	0.08	0.07
1955-64	0.13	0.13	0.10
1965-74	0.17	0.15	0.15
1975-84	0.19	0.17	0.20
1985-94	0.18	0.20	0.22
1995-2004	0.12	0.12	0.13
2005-15	0.11	0.11	0.12
Female	0.52	0.51	0.51
Male	0.48	0.49	0.49
N	**6510**	**7277**	**5461**

Table 4: Summary of Cohorts

	2012	**2015**	**2019**
Mean Size	147.4	173.3	130.0
St. Dev	91.3	108.7	83.0
Max	342	394	280
Min	13	16	12

Table 5a: % change in income by cohort, 2012-2019

Education	Year left education	Gender	Average cohort size	Percentage change
Primary	2005-2014	F	14	75.5***
Primary	2005-2014	M	21	72***
Secondary	1995-2004	F	109	44.3***
Primary	1995-2004	M	32	42***
Secondary	Pre 1954	M	24	40.3***
Primary	1975-84	M	205	40.1***
Secondary	2005-2014	M	69	38.8***
Primary	1985-1994	F	108	35.2***
Secondary	1995-2004	M	77	34***
Secondary	1975-84	F	187	33.8***
3rd Level	1955-64	F	53	33.7***
3rd Level	1975-84	M	178	30***
Secondary	1985-1994	M	170	29.5***
3rd Level	1975-84	F	169	28.5***
Secondary	Pre 1954	F	65	27***
Secondary	1965-74	M	104	23***
Secondary	1985-1994	F	185	22.8***
Secondary	1975-84	M	127	22.3***
Primary	1955-64	M	309	19.9***
3rd Level	1985-1994	F	246	19.6***
Primary	1985-1994	M	129	19.1***
Primary	Pre 1954	F	276	18.6***
3rd Level	1985-1994	M	267	18.6***
Primary	1965-74	M	243	18.1***
Primary	1975-84	F	157	17.2***
3rd Level	2005-2014	F	209	16.8***
3rd Level	2005-2014	M	151	15.7***
Primary	Pre 1954	M	242	13.6***
Primary	1965-74	F	232	13***
3rd Level	1955-64	M	63	12.1***
Primary	1955-64	F	310	11.3***
Secondary	1965-74	F	153	11.1***
3rd Level	Pre 1954	M	22	10.9*
3rd Level	1995-2004	M	172	8.3***
Secondary	1955-64	F	91	7.8***
Secondary	2005-2014	F	88	7.5***
3rd Level	1965-74	M	132	4.1***
3rd Level	1995-2004	F	234	3.2***
Secondary	1955-64	M	59	1.3
Primary	1995-2004	F	21	-1.5
3rd Level	Pre 1954	F	23	-2.9
3rd Level	1965-74	F	109	-3.1**

Table 5b: % change in income by cohort, 2012-2015

Education	Year left education	Gender	Average cohort size	Percentage change
Secondary	Pre 1954	M	37	35.5***
Primary	2005-2014	M	30	30.5***
3rd Level	1955-64	F	73	29.1***
Primary	2005-2014	F	17	23.6**
Secondary	Pre 1954	F	79	23.4***
Secondary	1995-2004	F	118	16.3***
Primary	1995-2004	M	32	12***
Primary	1985-1994	F	111	11.8***
Secondary	2005-2014	M	78	11.6***
3rd Level	1975-84	M	211	11.6***
3rd Level	2005-2014	M	156	11.5***
Secondary	1995-2004	M	86	10.9***
Secondary	1985-1994	M	166	10.7***
3rd Level	2005-2014	F	201	9.7***
Primary	1955-64	F	367	9.6***
3rd Level	1955-64	M	88	8.8***
Primary	1965-74	M	305	8.6***
Primary	Pre 1954	M	294	8.4***
Primary	Pre 1954	F	328	8.1***
3rd Level	1985-1994	F	280	6.9***
Secondary	1975-84	M	156	6.3***
Secondary	1975-84	F	230	5.5***
3rd Level	1985-1994	M	294	5.2***
Primary	1955-64	M	368	5.1***
Primary	1985-1994	M	162	5.1***
Secondary	2005-2014	F	114	4.8***
3rd Level	Pre 1954	M	29	4.3*
Secondary	1985-1994	F	231	4.1***
Primary	1975-84	M	237	3.9***
3rd Level	1975-84	F	184	2.6***
Secondary	1955-64	M	71	1.8*
3rd Level	1995-2004	F	239	0.9**
3rd Level	1995-2004	M	178	-1**
Secondary	1965-74	M	115	-1.8**
Primary	1965-74	F	286	-1.8***
Secondary	1965-74	F	175	-3.4***
Primary	1975-84	F	181	-4.3***
3rd Level	1965-74	F	117	-5.4***
Primary	1995-2004	F	19	-5.5**
Secondary	1955-64	F	125	-6.1***
3rd Level	Pre 1954	F	28	-10.7***
3rd Level	1965-74	M	147	-14***

Table 5c: % change in income by cohort, 2015-2019

Education	Year left education	Gender	Average cohort size	Percentage change
Primary	2005-2014	F	17	42***
Primary	1975-84	M	223	34.8***
Primary	2005-2014	M	25	31.7***
Secondary	1975-84	F	210	26.9***
Primary	1995-2004	M	35	26.8***
Secondary	1965-74	M	120	25.3***
3rd Level	1975-84	F	191	25.2***
Secondary	2005-2014	M	58	24.4***
Secondary	1995-2004	F	94	24***
Primary	1975-84	F	170	22.4***
3rd Level	1965-74	M	158	21.1***
Primary	1985-1994	F	104	20.9***
Secondary	1995-2004	M	80	20.8***
Secondary	1985-1994	F	219	17.9***
Secondary	1985-1994	M	181	17***
3rd Level	1975-84	M	210	16.5***
Secondary	1975-84	M	151	15.1***
Primary	1965-74	F	270	15.1***
Secondary	1965-74	F	179	15***
Secondary	1955-64	F	110	14.8***
Primary	1955-64	M	335	14.1***
Primary	1985-1994	M	154	13.3***
3rd Level	1985-1994	M	287	12.8***
3rd Level	1985-1994	F	287	11.8***
Primary	Pre 1954	F	265	9.7***
3rd Level	1995-2004	M	204	9.4***
Primary	1965-74	M	280	8.8***
3rd Level	Pre 1954	F	19	8.7*
3rd Level	2005-2014	F	221	6.5***
3rd Level	Pre 1954	M	19	6.3
Primary	Pre 1954	M	252	4.8***
Primary	1995-2004	F	18	4.2
3rd Level	2005-2014	M	155	3.8***
Secondary	Pre 1954	M	33	3.6
3rd Level	1955-64	F	57	3.6
3rd Level	1955-64	M	72	3*
Secondary	Pre 1954	F	57	2.9*
Secondary	2005-2014	F	89	2.5**
3rd Level	1965-74	F	118	2.5**
3rd Level	1995-2004	F	248	2.3***
Primary	1955-64	F	337	1.5***
Secondary	1955-64	M	66	-0.5

Figure 1a: Anonymous GIC, 2012-2018

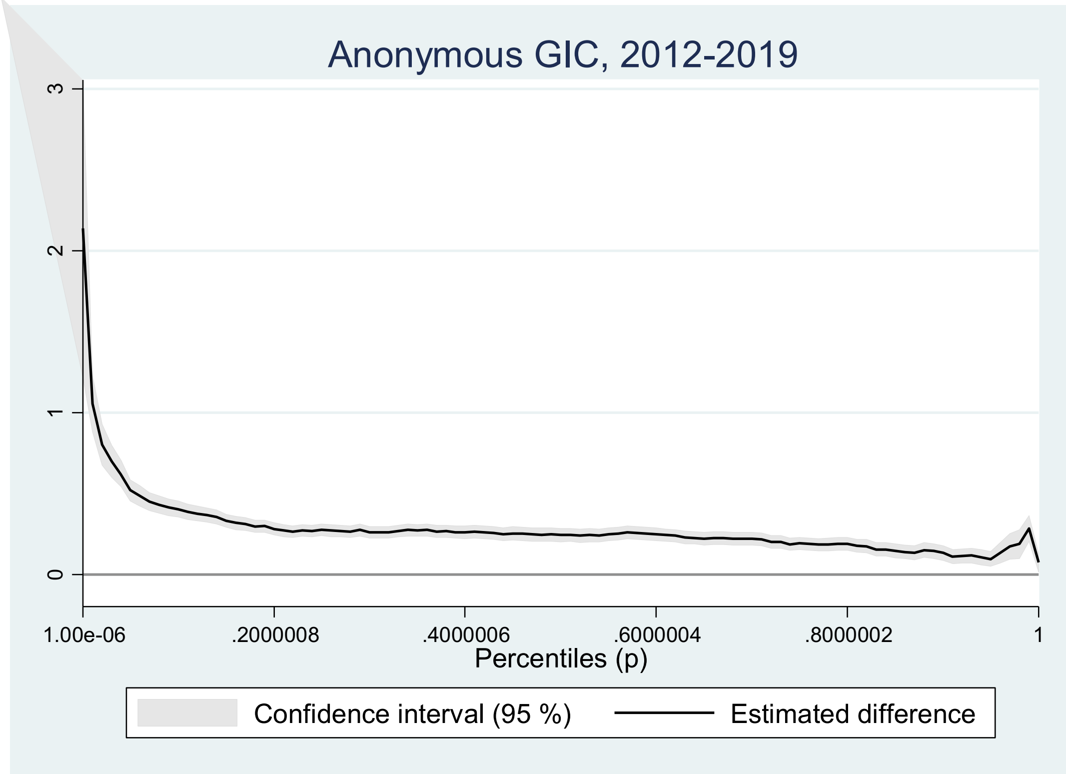


Figure 1b: Anonymous GIC, 2012-2015

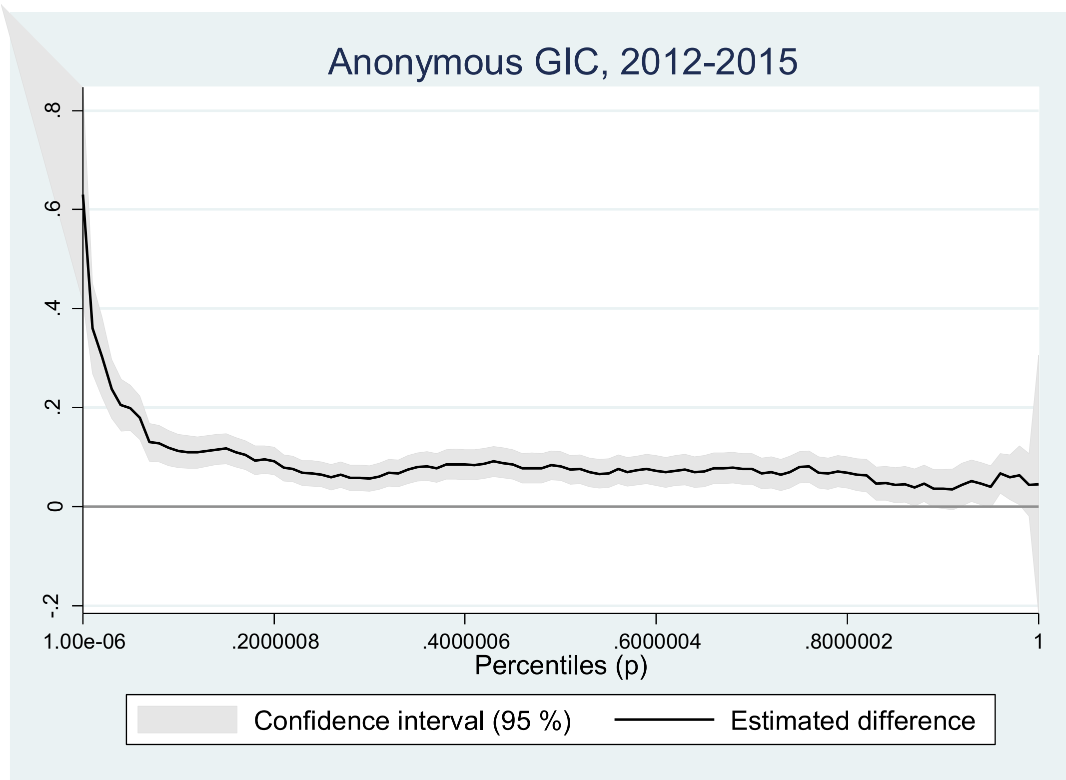


Figure 1c: Anonymous GIC, 2015-2018

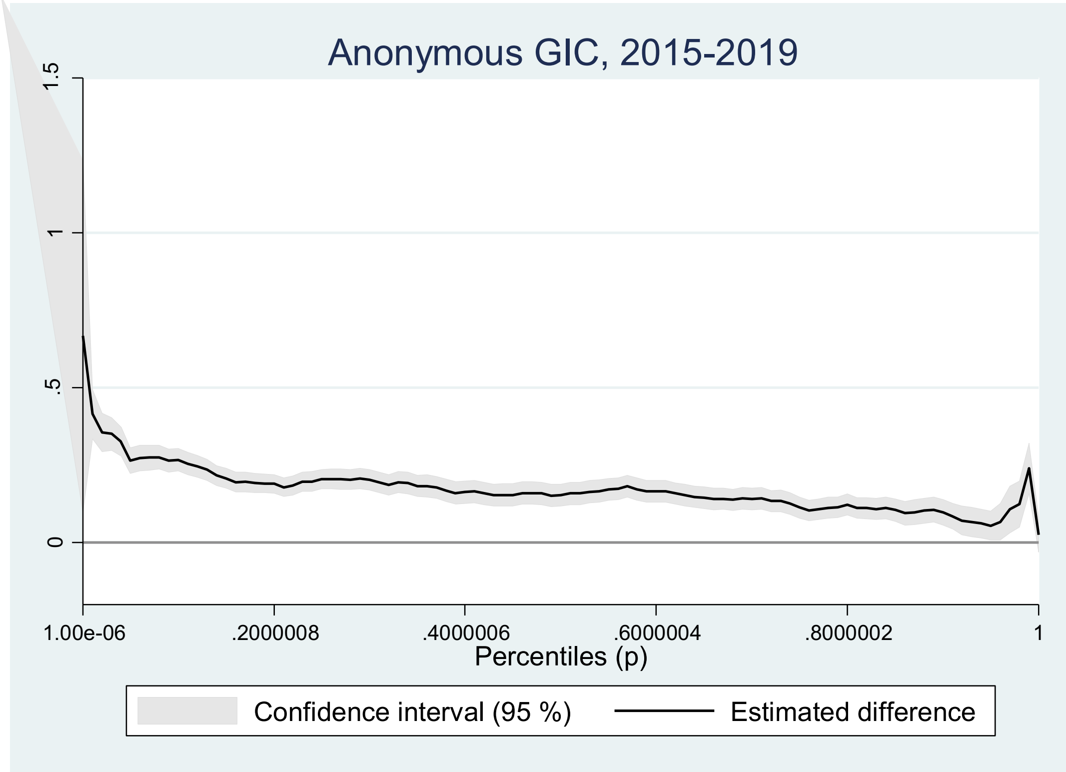


Figure 2a: Non-anonymous GIC, 2012-2019

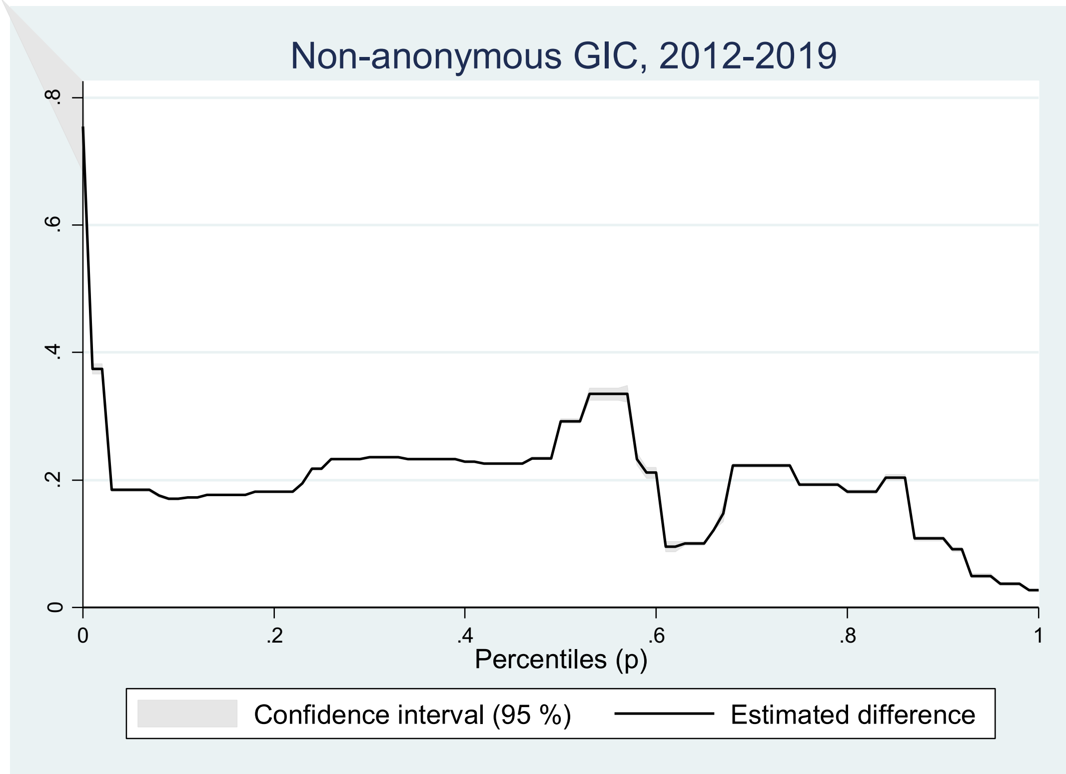


Figure 2b: Non-anonymous GIC, 2012-2015

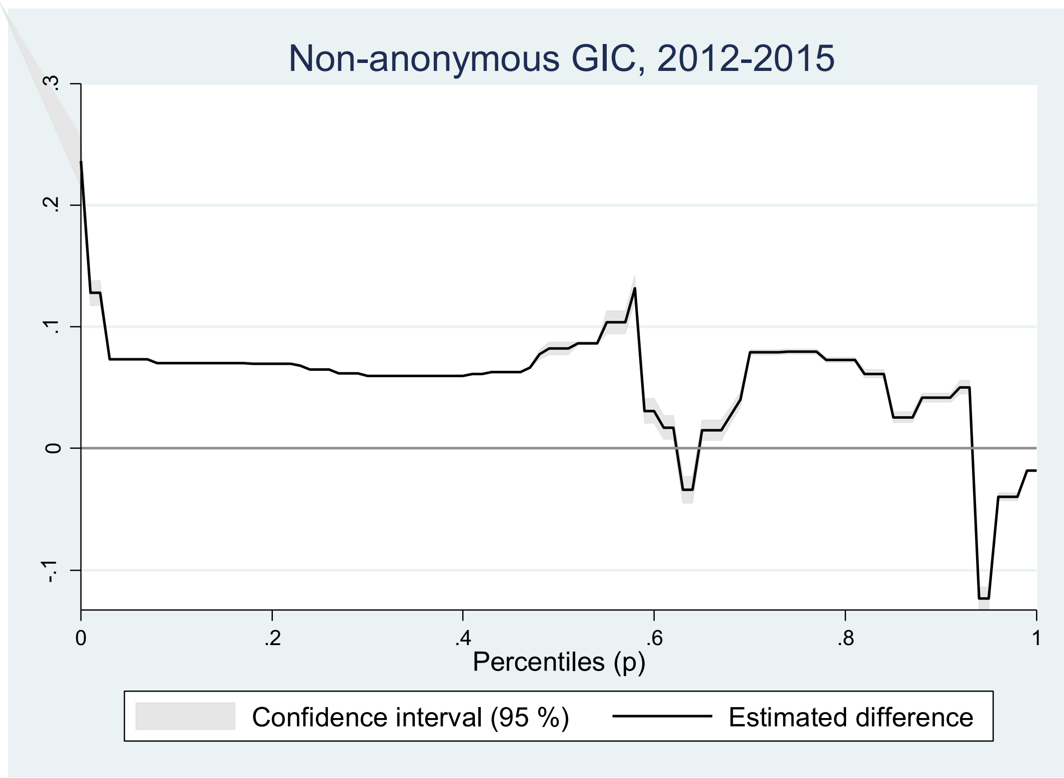
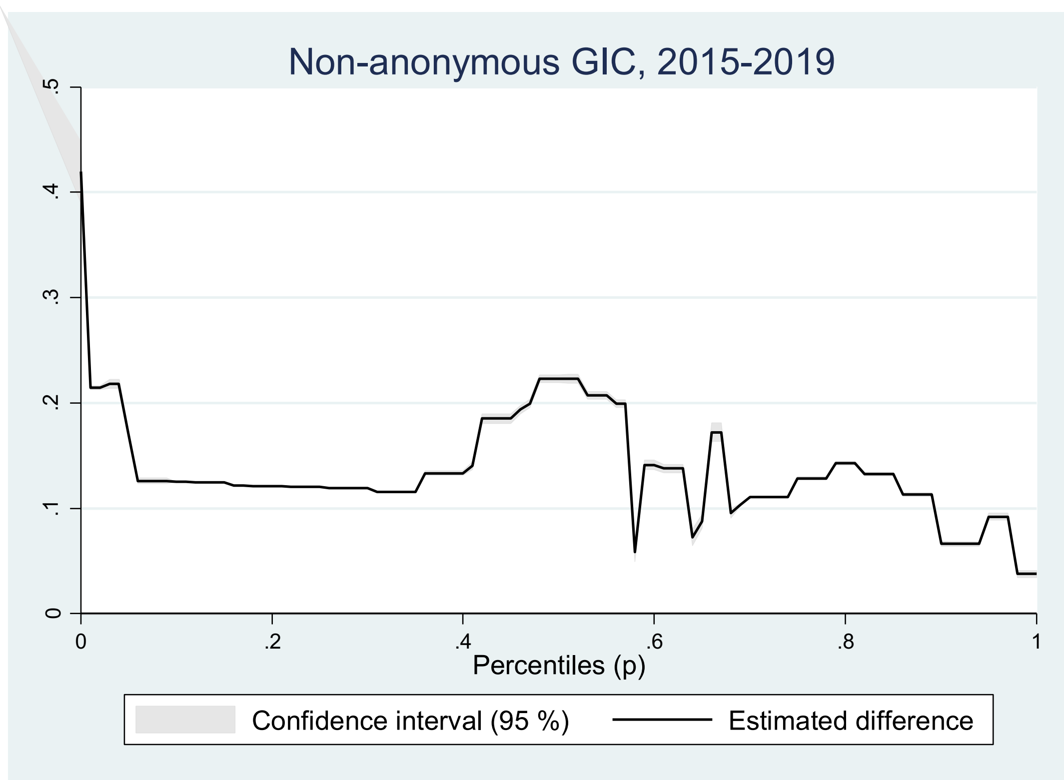


Figure 2c: Non-anonymous GIC, 2015-2019



Appendix 1: Definition of Income in SILC

Definition of Income: The income measure we use from SILC is equivalised income after social transfers using the EU definition of income and the modified OECD equivalence scale. The EU definition of income consists of:

- Direct income (employee cash and non-cash income)
- Gross cash benefits or losses from self-employment
- Other direct income (but not pensions from individual private plans, value of goods produced for own consumption, employer's social insurance contributions)
- All social transfers (e.g. unemployment benefits, housing allowances, sickness allowances etc).

Tax on income and contributions to state and occupational pensions are deducted from this to give disposable income, which is then adjusted to equivalised income by applying the modified OECD scale (1.0 first adult, 0.5 other adults, 0.3 children aged less than 14). For details see CSO (2007).

Appendix table 1: estimating sample versus full sample

	2012		2015		2019	
	Full	**Est**	**Full**	**Est**	**Full**	**Est**
Age						
0-17	0.247	0.000	0.247	0.000	0.238	0.000
18-64	0.633	0.784	0.622	0.753	0.620	0.715
Over 65	0.120	0.216	0.131	0.247	0.142	0.285
Male	0.490	0.483	0.490	0.493	0.491	0.492
Ed						
Primary	0.325	0.387	0.295	0.366	0.264	0.341
Secondary	0.321	0.272	0.326	0.275	0.300	0.260
Tertiary	0.353	0.340	0.379	0.359	0.436	0.399
PES						
Working	0.354	0.488	0.390	0.511	0.426	0.526
Unemp	0.091	0.116	0.056	0.069	0.039	0.041
Full time Ed	0.079	0.002	0.077	0.002	0.070	0.000
Home Duties	0.113	0.181	0.100	0.162	0.075	0.125
Retired	0.087	0.152	0.094	0.175	0.114	0.225
Ill/Disabled	0.037	0.051	0.041	0.069	0.010	0.071
Not yet working/other	0.230	0.008	0.242	0.011	0.224	0.011
N	11891	6191	13793	7277	10698	5461

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