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The Great Irish (De)Leveraging 2005-14

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Non-Technical Summary

The Great Recession highlighted the importance of the link between household balance sheets and the macroeconomy. Understanding household over-indebtedness is important for developing effective policy responses to issues such as mortgage arrears, as well as for informing views on the extent to which balance sheet developments affect aggregate spending and therefore the path of economic recovery.

Starting with the 2013 Household Finance and Consumption Survey (HFCS), this paper uses a combination of micro and macro data to simulate changes in household balance sheets from 2006 to 2014; we call this simulated household dataset 'HFCS-SIM'. The microdata used includes granular datasets on loans and incomes which allow the rich heterogeneity of the HFCS distributions to be traced over time. The dataset can be used to answer questions, such as: were certain households more or less affected by the property crash; have recent house price and labour market trends reversed any of the damage; and which households remain sensitive to macroeconomic shocks in the future?

HFCS-SIM shows that the decline in the wealth-to-income ratio since 2006 has been largest for older age-groups (aged 65 and above) who tend to have lower disposable incomes on average, but also a greater concentration of their wealth in property. The property crash also substantially reduced wealth at the bottom end of the wealth distribution, driving the bottom 20% of households into negative net asset positions. The bulk of these negative equity households are found in the younger cohorts who bought around the peak of the property market.

The dramatic decline in aggregate debt since 2007 is often cited as an indicator that households have been deleveraging in recent years. However, once we take account of the falls in income over the same period and differences in amortisation profiles, a very different picture emerges. Younger households – those born after 1969 – saw large increases in their debt-to-income ratios from 2006 through to 2010 rising by around 75 percentage points, a result of both declining disposable income for these groups and rising debt levels. Furthermore, these households have only seen very small falls in leverage ratios since 2010, which we attribute to weak disposable income growth and the slow amortisation rates arising from long mortgage terms and very high debt levels. Our results suggest that deleveraging for these younger households still has some way to go, and relies heavily on both income growth and increases in property prices.

We use the simulated dataset to examine the factors which impact on households' ability to service their mortgage debt. We show that income shocks are the main factor which lead to mortgage repayment problems. However, there is also a role for equity factors, whereby households in deep negative equity are significantly more likely to miss a payment, *and* the missed payment is more likely to remain outstanding for a longer period of time. We associate positive changes in some of these factors with the decline in mortgage arrears observed in recent quarters.

The Great Irish (De)Leveraging 2005-14 *

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Abstract

Drawing on the 2013 Household Finance and Consumption Survey (HFCS) and complementary administrative data sources, we simulate household balance sheets at the *micro* level for the 2005-14 period. We use this dataset to tell the story of household leveraging and deleveraging over a tumultuous period for the Irish economy. We show that deleveraging has proceeded at a signficantly faster pace for older households, when compared with younger age groups. In contrast, we find that a higher-incidence of tracker mortgages amongst younger borrowers – which passed through the historically low ECB policy rates since 2009 – relative to older borrowers has played a major role in easing the debt repayment burden in the presence of large income shocks. Notwithstanding historically low interest rates, we show that income shocks are the main factor contributing to mortgage repayment problems. However, there is also a role for equity factors.

JEL Classification: D12, D31, E21
Keywords: Households, Debt, Assets, Income, Deleveraging.

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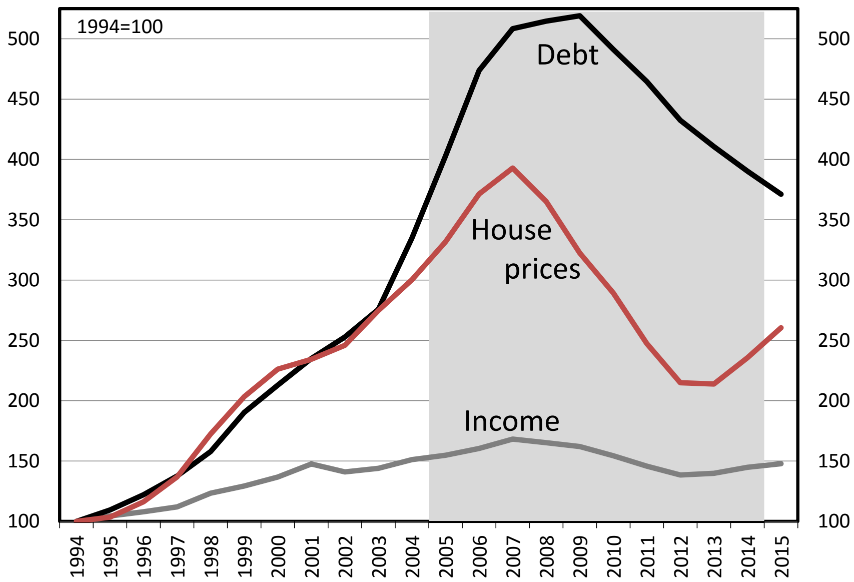
1 Introduction

The Irish economic experience in the 2000s was extraordinary in terms of the scale of the boom and the subsequent bust. From the early-2000s through to the peak of the property boom in 2007, growth in household debt far outstripped growth in disposable income as home-buyers chased ever-increasing house prices with easy-to-come-by credit (see Figure 1). The rapid increase in leverage ratios and repayment burdens left households exceptionally vulnerable to the economic shock which was to hit in 2008. The ensuing financial crisis engulfed all sectors of the economy, from households to firms, and from banks to the sovereign. From 2008 to 2012, employment fell by 15%, house prices plummeted by 55% and net disposable incomes, eroded by job losses, pay cuts and tax increases, declined by 16%. For households, another notable crisis-related outcome was the large increase in non-performing mortgage loans. At the peak, in mid-2013, almost one-quarter of residential owner-occupier mortgages were in arrears – 17% for 90-days or more.

This paper uses micro data on household balance sheets and incomes to understand how different households were affected by the crisis. Taking the 2013 Household Finance and Consumption Survey (HFCS) as a starting point, we draw on a range of administrative datasets and macro data to simulate household balance sheets at the micro level. The dataset, which we label HFCS-SIM, spans 2005 to 2014, covering both the last few years of the credit boom and the long deleveraging that followed (see shaded area in Figure 1).

Figure 1: House prices, income and debt over time



Source: Authors' calculations using CSO data.

Our micro data complements existing aggregate databases, such as the Quarterly Financial Accounts (QFA). However, unlike the QFA, HFCS-SIM helps us to understand how the *heterogenous* nature of household balance sheets affects aggregate economic activity. For example, HFCS-SIM clearly identifies which groups needed to deleverage, and why. In this context, understanding the intersection of income and asset price shocks, particularly for highly indebted households, is crucial. HFCS-SIM also highlights how some borrowers disproportionately benefitted from one of the major policy responses to the crisis namely, the reduction in ECB policy rates to historic lows. These reductions were fully passed through to borrowers with tracker loans – typically, the youngest and most highly indebted groups – significantly easing their debt repayment burden, even in the presence of negative income shocks; whilst other borrowers with fixed and standard variable (i.e. non-tracker) rate loans saw much less of a benefit.

Notwithstanding interest rate cuts which contributed to a reduction in mortgage repayments for a subgroup of borrowers, the scale of the negative income shock, combined with a high debt burden, led to significant repayment problems. For some households, reduced repayments via a renegotiation of mortgage terms – typically moving to interest only (IO) repayments or an extension of the loan term – provided sufficient breathing space. However, as the crisis wore on, more and more households went into deep mortgage arrears. The income component of HFCS-SIM, which is comprised of administrative panel data on earnings from work for HFCS individuals, sheds a new light on debt distress in Ireland during this period. Contributing to an already rich literature on the determinants of mortgage arrears (see Deng et al. (2000) and Gerardi et al. (2015), for example) we show how income, equity and other borrower characteristics contribute to debt repayment problems.

This paper contributes to a wider literature analysing how household balance sheets affect the economy; see, Krimmel et al. (2013) for the US and Ampudia et al. (2016) for the Euro area.[1] However, unlike most other papers that use *aggregate* data to 'age' balance sheets, we primarily use *micro* datasets to both generate and cross-check our simulated datasets. This means that instead of just shifting distributions around a mean, and ignoring the differential impact that shocks might have on households in different parts of the asset, debt or income distributions, we are able simulate changes across the entire distribution. For certain applications, such as understanding the sources of mortgage repayment problems, and where accurate information on income shocks in the tails of the indebted households distribution are particularly important, these distributional data are vital.

The remainder of this paper proceeds as follows. Sections 2 and 3 describe the raw data and the construction of HFCS-SIM. Section 4 describes the trends in household leverage in Ireland between 2005 and 2014. Section 5 examines the drivers of mortgage repayment problems. Section 6 concludes.

[1] It also shares a heritage with an earlier generation of micro-simulation studies that are used for tax-benefit modelling; see, for example, Giles and McCrae (1995).

2 The HFCS and other data used in the analysis

2.1 The Irish Household Finance and Consumption Survey (HFCS)

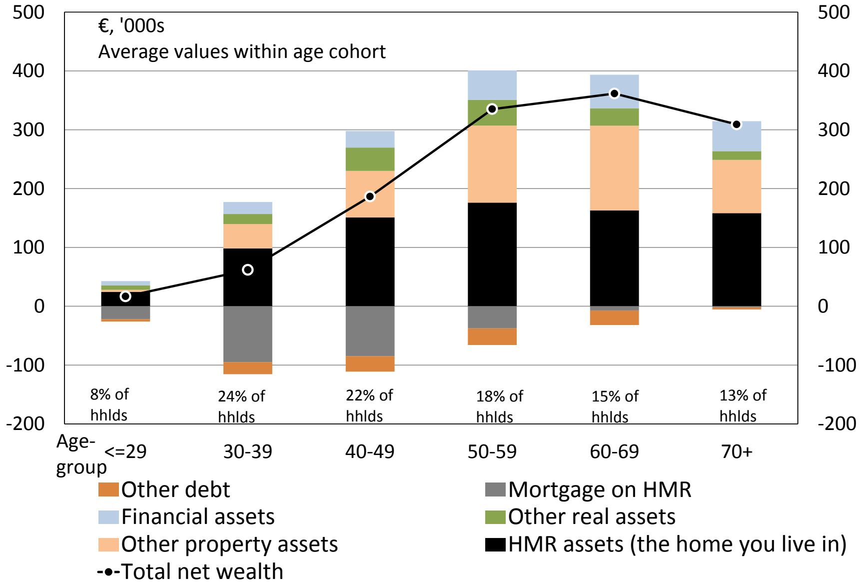
The 2013 HFCS was carried out as part of the Household Finance and Consumption research Network within the European System of Central Banks. Fieldwork was carried out by the Irish Central Statistics Office (CSO) between March and September 2013. In total, 5,419 households and 14,546 individuals completed the survey.[2] Compared to existing CSO household surveys which cover income (SILC) and employment (QNHS), the major innovation in the HFCS is the collection of data on gross wealth and debt.

Figure 2 shows average debt and assets for different age groups. With a view to the microsimulation to follow, a number of key patterns emerge. First is the predominance of the *Household Main Residence* or 'HMR' (i.e. the home you live in) in both assets and debts. It accounts for the bulk of gross asset wealth; 71% of Irish households are home-owners. Mortgage debt also accounts for the largest share of household debt, declining with age.

The second thing to note is the non-negligiable share of 'Other property assets' in total assets, particularly for middle- and older-aged groups. This category consists of both residential investment property (buy-to-lets) and business property, with the latter accounting for the largest share. Within business property assets, farm land accounts for the bulk of asset wealth.

[2] See (Lawless et al., 2015; Central Statistics Office, 2015) for more on the background on the survey, including detailed results.

Figure 2: Average wealth and debt by age-group, 2013



Source: HFCS 2013.

2.2 Additional data sources

Loan-level Data (LLD, Central Bank of Ireland)

The LLD has been collected by the Central Bank of Ireland (CBI) from retail banks since 2010. The data contains information on loan characteristics for each loan, as well as some data relating to the collateral, such as value at loan origination, property type and location. The data covers approximately 80% of loans in the population. Kennedy and McIndoe-Calder (2011) has a detailed data description. In this paper, we use the LLD to cross-check our imputed property values and debt distributions.

Quarterly Financial Accounts (QFA, Central Bank of Ireland)

The QFA compiles information on the aggregate assets and liabilities of the household sector since 2002. In this paper we use the QFA to cross-check our simulated property and financial asset values.

Money and Banking Statistics (MBS, Central Bank of Ireland)

The MBS measure the liabilities and assets of all credit institutions within the State. In this paper we use the MBS to age the largest component of financial assets: savings and deposits; to validate the property debt simulation; and, to age households' non-collaterlised debts.

Administrative data on earnings from work (TAX, CSO)

The earnings data we use is taken from an administrative tax database on the annual earnings of employees in Ireland from 2005 through to 2014, provided by the CSO. The tax database is linked to individuals in the HFCS allowing us to construct individual level income profiles over the period of interest. Lydon and Lozej (2016), contains a detailed overview of the data.

Survey of Income and Living Standards (SILC, CSO)

SILC is the definitive source of survey information on household incomes. We use SILC to age the income from work of self-employed individuals and to cross-check our imputed income from social transfers in HFCS-SIM.

3 Construction of HFCS-SIM

This section sets out our approach to constructing each of the main components of HFCS-SIM: assets, liabilities and income. The general approach involves two steps: (1) Identify a suitable micro data source (which could include information in the HFCS itself) to age the variable of interest; (2) Verify and cross-check the imputed distributions using another data source. If no suitable micro data source exists for step (1), aggregate data are used, which is the approach most widely used in the literature (Krimmel et al., 2013). Table 1 provides an overview of the simulation methodology and data source used for each component of the HFCS.

Table 1: Simulation: techniques, data sources and robustness

	Simulation		Robustness	
HFCS component	Technique/Data	Source	Data	Source
Assets				
Property				
HMR	Time varying hedonic regression	HFCS (CSO)	LLD RPPI QFA	CBI CSO CBI
Other residential	RPPI	CSO; Dallas Federal Reserve; OECD	QFA	CBI
Commercial	Land price index; Commercial property price index	SCSI/Teagasc MSCI	QFA	CBI
Non property real assets				
Vehicles	Depreciation rate	AA Ireland		
Other	Assumed constant	Authors		
Financial assets				
Savings and deposits	Term deposit index	MBS (CBI)	QFA	CBI
Equities	ISEQ	ISEQ	QFA	CBI
Bonds	QFA	CBI		
Pensions	FTSE	FTSE	QFA	CBI
Debts				
HMR	Loan characteristics (accounting for interest rate & top up evolution)	HFCS (CSO)	LLD MBS	CBI CBI
Other property	Loan characteristics (accounting for interest rate & top up evolution)	HFCS (CSO)	LLD	CBI
Non-collaterlised debt	MBS	CBI		
Income				
Employment	Tax	CSO	SILC	CSO
Unemployment	Tax	CSO	SILC	CSO
Self-employment	Self-employed income	SILC (CSO)		
Inactive - Pension	Tax	CSO	SILC	CSO
Inactive - Other	EU-SILC	CSO	SILC	CSO

Note: Central Bank of Ireland (CBI) sources: Quarterly Financial Accounts (QFA); Loan-level data (LLD); Money and Banking Statistics (MBS). CSO sources: Household Finance and Consumption Survey (HFCS); Survey of Income and Living Standards (EU-SILC); Administrative tax data (Tax); Residential Property Price Index (RPPI); Other sources: Teagasc, FTSE, ISEQ, SCSI IPD, MSCI.

3.1 Gross Assets

Gross assets consist of property (77.6%), Other real assets (9.7%), and Financial assets (12.7%). Property assets can be split into the household main residence (HMR, 47.8%); other residential property including buy-to-let (BTL) and holiday homes (7.5%); and other property, including farm land and business/commercial property (22.3%).

Household Main Residence (HMR)

HFCS homeowners are asked "How much was the residence worth at the time you acquired it?" We use the answer to this question as the dependent variable in the following regression:

$$log(HP_{i,2013}^{Y|\text{purchase year Y}}) = \alpha + \beta_{loc}Loc_i + \beta_{type}Type_i + \beta_{size}Size_i \tag{1}$$

where the subscript *2013* refers to the fact that households are asked in 2013 to recall the value of a house acquired in year Y. The Loc variable interacts region (NUTS III, n=8) with 'location' i.e., downtown; area between city centre and suburbs; town outskirts; and isolated area, countryside. $Type$ refers to the type of dwelling: individual house; semi-detached house; flat/apartment; and other kind of dwelling. Finally, $Size$ controls for the square meterage of the property. All parameters can vary by year. The imputed house value in any given year is the fitted value from the hedonic regression, conditional on the household being a homeowner in that year, which is known in the HFCS.

If the property was acquired during the 2005-2012 simulation period (27% of homeowners), the reported purchase price replaces the regression fitted value. House prices in 2014 and 2015 are generated using actual house price changes at the Dublin/non-Dublin, Apartment/non-apartment level from CSO house price data.[3] If the purchaser is under-35 in the purchase year we assume they are First Time Buyers (FTBs).[4] For those over 35 in the year of property purchase, we assume they traded-up in the past

[3] The HFCS contains no transactions for 2014 and 2015, having been carried out in 2013, thus hedonic regressions cannot be estimated for simulation in these two years.

[4] Using CBI LLD from 2000 to 2006, Coates et al. (2015) report a median first-time buyer age of 32.

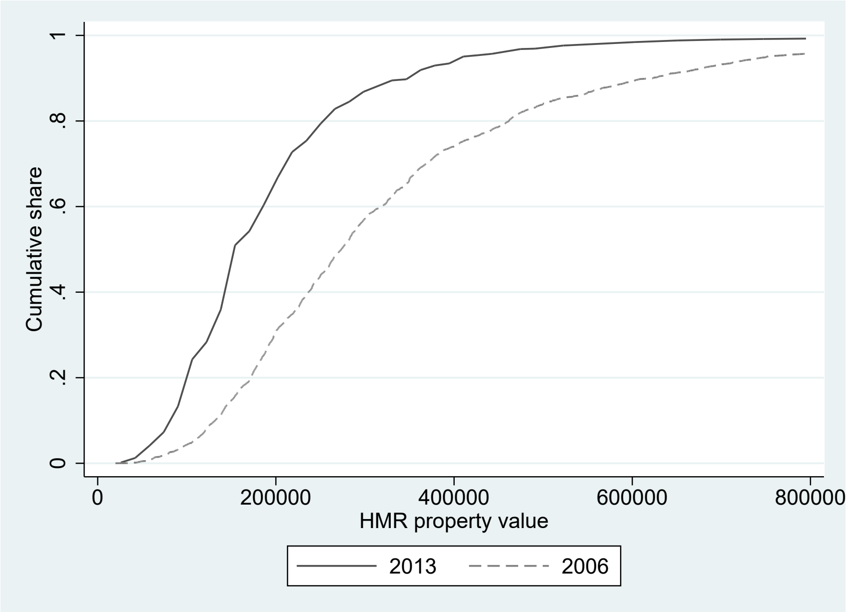
and previously owned a home equal to the average value of FTB properties in the area/year.

The fit is generally good for the hedonic regressions, with an R-squared of around 0.7 in each year (results available on request). The coefficient on size tends to be the most important predictive variable, although most right hand side variables are statistically significant.

Recall bias in house purchase prices could lead to measurement error in the dependent variable. Therefore, as a robustness check, we also simulate prices using average year-on-year property price changes for twenty quantiles of the price distribution, controlling for house type (detached, semi-detached/terraced and apartments) and region (Dublin/Non-Dublin). The house price database comes from reported valuations at the time of acquisition in the LLD. Perhaps not surprisingly, we find that this second approach results in house price distributions almost *identical* to those generated by the hedonic approach; in the analysis that follows, therefore, we use the hedonic results. Figure A1 in the appendix shows that growth in mean house prices in our simulated data closely tracks the CSO residential property price index.

Figure 3 shows the (cumulative) distribution of reported HMR house values in the HFCS in 2013 and the simulated distribution in 2006. It is a stark illustration of the scale of the asset price shock households experienced as a result of the 55% peak-to-trough fall in house prices in Ireland. At the top of the distribution (top 80% of values) the nominal euro-value fall is over €200,000; at the bottom-end (bottom 20%) the fall is approximately €70,000.

Figure 3: CDF nominal house values 2006 versus 2013



Source: HFCS-SIM (2017).

Other residential property

In the HFCS, 10% of households own another residential property, accounting for 7.5% of gross assets held by households. The propensity for owning other residential property increases the further up the income or wealth distribution you go, with 26% of households in the top income quintile claiming ownership of another residential property asset (Lawless et al., 2015). The HFCS records information on property location (including in Ireland (85%) or abroad), when it was acquired and purpose, i.e. holiday home or BTL. For Irish properties we update house values by using the Residential Retail Property Price Index (Central Statistics Office, 2016), unless the purchase occurs during 2006-12, in which case we use the purchase prices. For non-Irish, residential property we update the values using country-specific annual nominal house price indices from Federal Reserve Bank of Dallas (2016)[5] and OECD (2016).

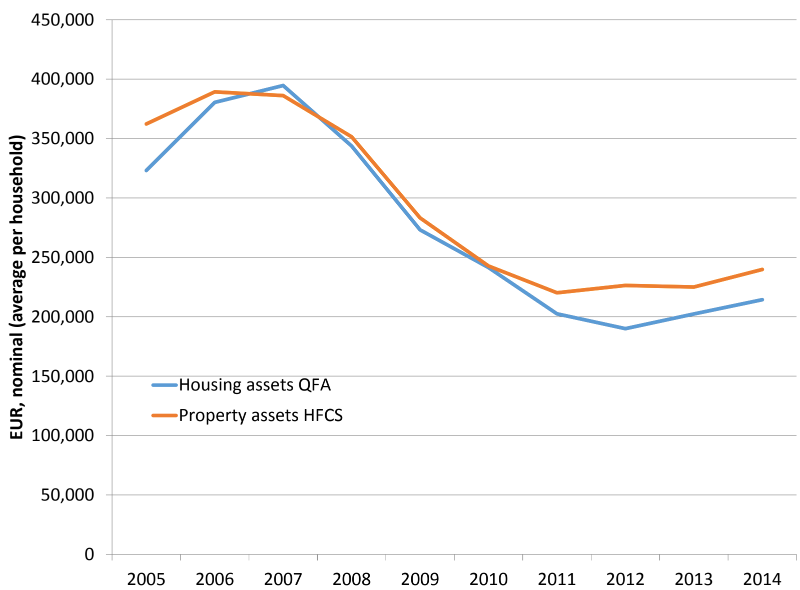
[5] The authors acknowledge use of the dataset described in Mack and Martnez-Garca (2016).

Other non-residential property

In the 2013 HFCS, over three-quarters of non-residential property holdings are farming assets (90% share by value). Land values are aged using an annual database on agricultural land prices at the regional level (Society of Chartered Surveyors Ireland and Teagasc, 2016). Commercial property holdings are categorised into retail, offices and industrial – with over half of holdings in the latter – and aged using the MSCI (2016) commercial property price index.

Figure 4 brings together all of the simulated property asset values in HFCS-SIM and compares them with the QFA. The two categories may not be exactly like-for-like, in particular it is not clear how commercial property is treated in the QFA. Nonetheless, the household means of the two series are very close, providing additional support for our simulation methodology.

Figure 4: Average value of housing assets (QFA) *versus* Average value of property assets (HFCS-SIM)



Source: HFCS-SIM (2017), Central Bank of Ireland (2015).

Financial Assets

Financial assets are naturally more liquid than real assets such as property, thereby increasing the likelihood of households substituting between different financial assets. Outside of the 2013 HFCS, however, there is no other source of household-level data on holdings of financial assets. Therefore, here we adopt a 'top-down' approach, which the simplifying assumption that the household financial asset portfolio mix remains constant over time. The value of each component is aged as follows:

- *Savings and deposits* – 90% of households, 55% of financial wealth – we adjust the distribution according the changes in the total stock of overnight and term deposits from Table A18 of the Central Bank of Ireland Money and Banking Statistics (Central Bank of Ireland, 2016).
- *Equities* – 13% of households, 10% of financial wealth – indexed to changes in the Irish Stock Exchange Index (ISEQ).
- *Bond holdings* – 4.5% of households, 2.3% of financial wealth – indexed to changes in the total value of holdings of securities other than shares from the QFA.
- *Pensions and other financial assets* – 11% of households, 32.7% of financial wealth – indexed to changes in the FTSE all world index.[6]

Comparing the trend in our simulated Financial Assets series with those in the QFA (index values to 2006=100) is less favourable than that for property assets (Figure A2), although the two series are still highly correlated (correlation coefficient of 0.70).

Other (non-property) real assets

Non-property assets, consisting mainly of vehicles and business-related assets, account for 9.7% of gross assets. In the simulation, vehicle values are assumed to depreciate at 16% per annum, and are capped at the average value of new vehicles purchased by households in 2012-13, controlling for income and family size.[7] Business-related assets cover items such as machinery, equipment and the value of stocks; agricultural equipment also plays an important role here. For the current simulation we hold these

[6] Irish Pension fund returns are strongly correlated (correlation coefficient = 0.97 from 2009-14) with world indices of equity returns such as the FTSE All World Index. See, for example, the AON Hewitt quarterly pension funds survey.

[7] The 16% assumed depreciation rate is the mid-point of a range of values provided by theaa.com

value constant at 2013 levels. Finally, there is a catch-all category of 'Other' valuables covering a wide range of items, such as jewellary, antiques, works of art and electrical items; and account for less than 2% of wealth. We also hold these values constant at 2013 levels.

3.2 Household debt – HMR mortgage debt

Debt consists of HMR mortgage debt (71.6%), other property mortgages (22.6%) and non-collateralised debt (5.8%). We roll back mortgage repayments and the stock of outstanding mortgage debt according to the following amortisation formula:

$$c_t = (i_t * P_t)/(1 - (1 + i_t)^{-Term_t}) \tag{2}$$

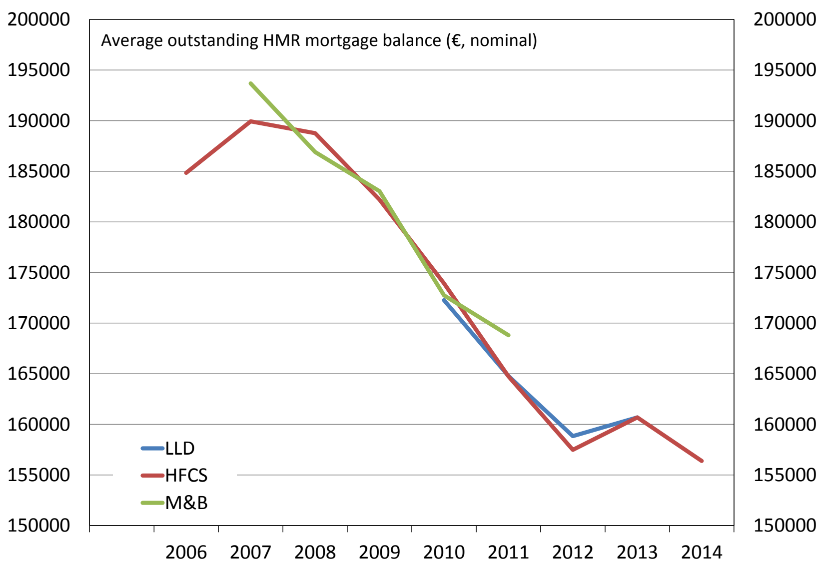
where c_t is the monthly repayment, i_t the interest rate, P_t the outstanding balance and $Term$ the term remaining (in months). Outstanding balance is calculated as follows:

$$P_t = ((P_{t+1} + 12 * c_{t+1})/(1 + i_{t+1})) - topups_{t+1} \tag{3}$$

We control for mortgage renegotiations and other changes to mortgage terms (e.g. IO, term extentions, etc) which could affect repayments. We assume that the interest rate *type* in 2013 (fixed, standard variable rate or tracker mortgage) holds historically, and that the margin over the ECB policy rate is constant for tracker loans. For standard variable rate mortgages (i.e. non-tracker), we assume the margin over the ECB base rate is the same as the tracker margin up to 2009, and thereafter moves towards the observed 2013 margin in a straight-line transition. This assumption follows Goggin et al. (2012), who show that non-tracker variable rates were identical to tracker mortgage rates up to 2009, after which point lenders started to charge a higher margin on the former. In the sample of HFCS households with an HMR mortgage, 16% were purchased during the simulation period. We divide these households into under-35s – who we assume are FTBs and assign a zero pre-existing mortgage debt – and over-35s, who we assume are trading up and assign them a previous mortgage balance equal to the average FTB household in the sample, minus the deposit paid on the trade-up (known in the HFCS).

Comparisons with the LLD are supportive of our simulation approach (see Figure 5). For example, the LLD mean in 2010 (2013) is €172,000 (€160,000) compared to €174,000 (€161,000) in the HFCS data.

Figure 5: Average HMR mortgage debt in three datasets



Notes: 'LLD' refers to Cental Bank of Ireland Loan-Level Data; 'HFCS-SIM' is the simulated HFCS dataset; and 'M&B' is Central Bank of Ireland Money and Banking Statistics.

Other property mortgage debt

Other property mortgage debt includes both BTL and commercial property loans. The approach we adopt is similar to that for the HMR mortgage: roll back the debt using the annuity formula. There are strong similarities between the debt distributions in both LLD and HFCS with means in 2011 (2013) of €251,000 (€240,000) in the LLD compared to €237,000 (€220,000) in the HFCS-SIM data (See the appendix, Figure A3).

Non-collateralised debt

For non-collaterised debt we roll back the HFCS data using aggregate CBI Money and Banking Statistics (2015) trends. There are two reasons for adopting this 'top-down' approach. First, unlike collaterised debt, the HFCS contains very little information on the characteristics of non-collaterised debt. Second, to our knowledge, there is no available micro data source which would allow for a more bottom-up simulation.

3.3 Validation and changes in net wealth

As HFCS is currently the only granular data available on Irish household balance sheets, validation is challenging. Here, validation is carried out using the following criteria: is the component simulated using granular data; how do the mean and median of the simulated distribution compare to other granular data at specific points in time; how do the mean and median correlate with the data (granular or aggregate) over time; has the simulation technique used allowed aging of several moments in the underlying distribution; and the relative weight of each component in overall balance sheet/income position of households. Table 2 ranks our simulated HFCS components based on these criteria in order to asses how useful the simulated dataset is likely to be for specific applications. It is clear that those balance sheet components that carry the heaviest weight in making up the overall net wealth of households have benefited from simulation of several moments using complementary granular data which will be important in analysing leverage and debt distress trends over time for different facets of the population.

Table 3 combines the simulated historic values for assets and debt to present a picture of changes in median net wealth from 2007 (the peak year for residential property prices) to 2013, by income and wealth quintile and decade born. The first set of columns show changes in total net wealth, the second set of columns show only net property wealth (conditional on owning property in 2007) – the largest element of household wealth (see Figure 6).

Across the middle-income groups – quintiles two, three and four – the percentage change in total net wealth is broadly similar, in the region of -45%. In the bottom of the income distribution, where property ownership rates are significantly lower, there is practically no change in net wealth from 2007 to 2013. In the top income quintile,

Table 2: Simulation of balance sheet items: quality criteria

HFCS component	Value 2013 (%)	Granular data	Comparison of means Point	Correl	Comparison of medians Points	Correl	Several moments aged[1]
Assets							
HMR	47.8	y	y	y	y	y	y
Other property	29.8	n	y	y	n	n	y
Non property real assets	*9.7*	n	n	n	n	n	y
Financial assets	*12.7*	n	y	y	n	n	y
Total	100						
Debts							
HMR	71.6	y	y	y	y	y	y
Other property	22.6	y	y	y	y	y	y
Non-collaterlised debt	5.8	n	n	n	n	n	n
Total	100						

[1] Where semi-granular data are used several strands of the underlying component may still be aged using several aggregate series, allowing more than one moment of the distribution to be simulated over time.

where households hold a more diversified portfolio (beyond property, that is), the fall in net wealth is also relatively less, at -38%. Similar patterns emerge when we look at changes in wealth by quintile of the 2007 wealth distribution. The least wealthy households where, by definition home ownership rates are lower, actually saw a small rise in median wealth levels, albeit from relatively low levels. Moving up the wealth distribution, the wealth losses are very similar, in the region of 45%. A very different picture emerges when we focus on households with property assets (the right-half of the table). First off, we see an increase in net wealth losses across the board, but in the bottom of the distribution the losses are now exceptionally large, at over 100% of initial property wealth.

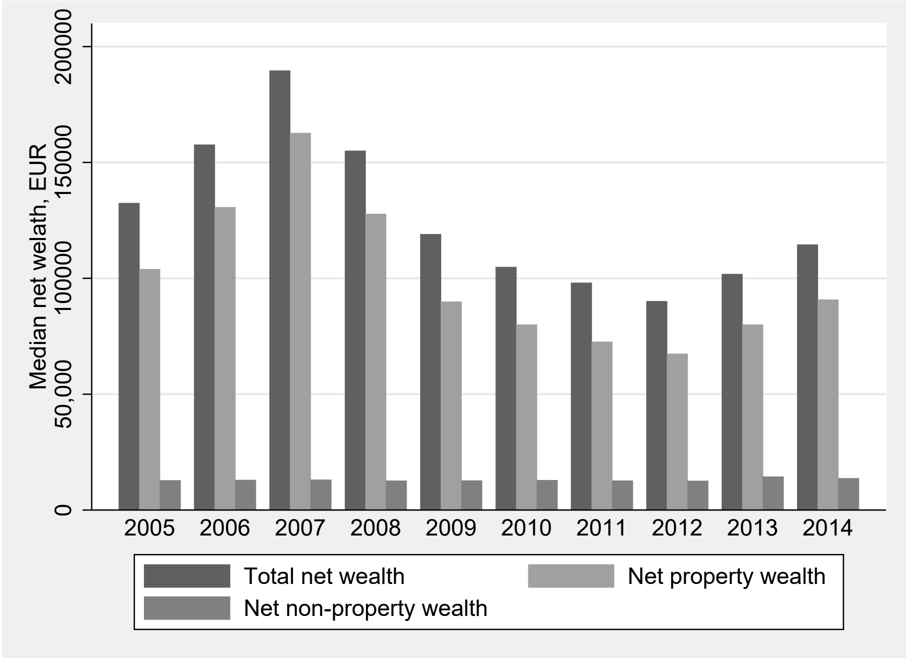
Nowhere is the picture of wealth destruction as a result of a property crash more clear than when we look at wealth losses by birth-decade. Younger households, that is, those born in the 1970s and 1980s, see almost all their wealth wiped out by the property crash. This is the result of large property price declines combined with high initial debt levels. We return to this theme in the section below which looks at deleveraging, income shocks and the repayment burden.

Table 3: Median net wealth, 2007 -v- 2013 (current prices)

	Net wealth All households			Net property wealth Property owners (in 2007 & 2013)		
	2007	2013	% change	2007	2013	% change
Income quintile in 2007						
1	10,709	10,800	1%	242,530	121,000	-50%
2	129,086	75,996	-41%	270,322	140,000	-48%
3	184,007	99,200	-46%	276,979	135,000	-51%
4	246,588	135,000	-45%	273,201	140,000	-49%
5	416,841	256,750	-38%	378,098	198,000	-48%
Net wealth in 2007						
1	465	700	50%	70,668	-3,165	-104%
2	21,865	13,100	-40%	185,711	90,000	-52%
3	189,612	99,000	-48%	288,682	150,000	-48%
4	366,338	201,500	-45%	462,601	240,000	-48%
5	916,753	528,266	-42%	1,071,079	534,000	-50%
Decade born						
pre-1950s	354,693	201,500	-43%	353,315	180,000	-49%
1950	348,437	195,500	-44%	353,006	180,000	-49%
1960	255,789	135,842	-47%	288,597	145,000	-50%
1970	78,172	22,500	-71%	187,056	56,000	-70%
post-1970s	6,235	3,800	-39%	99,235	-20,000	-120%

Source: HFCS-SIM (2017).

Figure 6: Net wealth, by asset type (median))



Source: HFCS-SIM (2017).
Note: Not conditional on asset participation.

3.4 Household income

Using the simulated values for debt and assets, we can analyse changes in leverage ratios over time. However, this ignores an important aspect of household overindebtedness, namely how the debt repayment *burden* evolves over time. To calculate this, we need to simulate changes in household incomes to go alongside the debt repayments series described above.

The backbone of our income simulation is an adminstrative dataset on earnings from work, available from 2005 to 2014. These data, sourced from annual tax returns, contains information on weeks of work and annual earnings for *each individual* in the HFCS data. Private pensions paid by employers are also in this dataset. This allows individual level income shocks to be traced over time and is an important contribution to our understanding of household financial fragility during the recession.

For self-employed workers, who account for just-under 17% of all workers in 2013, we do not have an administrative dataset on income from work. Instead we group self-employed workers into four sectors: Agriculture (31% of self-employed workers from 2006-13, according to SILC), Construction (15%), Professional services (45%) and the Wholesale and Retail Trades (9%). Then, subject to being in work (which is known from the individual's work history), we adjust the 2013 HFCS values using the change in percentage median self-employment income for workers in these broad sectors from the SILC.

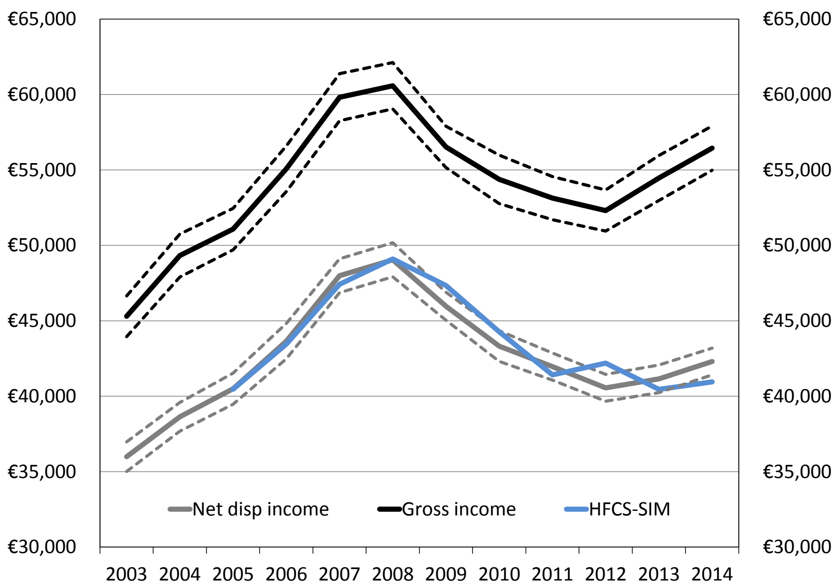
Inactive individuals account for almost 45% of survey respondents. This includes retirees, those with a long-term illness, students and home workers. For retirees, pension income is held constant at 2013 values, conditional on being at least 66 years of age in any given year. If individuals retire between 2006 and 2013, previous income from work is sourced from the administrative data. For those under 66 without pensions (15% of individuals over 16) we allocate to them the social transfers they are eligible for in each year using characteristics matched from EU-SILC.

To construct an annual figure for *disposable* income, we take full account of the significant tax changes (and social insurance contributions) during the period,[8] such as the introduction of various income levies throughout the crisis and the 'Universal Social Charge' (USC) in 2011.[9] We also estimate social transfer payments, controlling for household composition. Figure 7 shows that our simulated data closely track SILC trends.

[8] See Collins (2015) for a summary of tax changes since 2007.

[9] The USC brought a large number of previously untaxed households into the tax net and increased the tax burden for existing tax payers.

Figure 7: Average household income trends in SILC and HFCS-SIM (nominal, annual)



Source: Own calculations using SILC (CSO) and HFCS-SIM (2017). *Note:* 95% confidence intervals on SILC series shown.

4 Deleveraging, income shocks and repayments

Drawing on the information in HFCS-SIM, this section describes changes in household indebtedness over time. We focus on property-related debt. Not only does this constitute the bulk of households' debt but, as we demonstrated above, the historic simulated data closely track other granular sources. In addition to debt *levels*, we also look at the evolution of debt *repayments* relative to income. Since 2007, Irish households have experienced a significant decline in their disposable income due to a combination of job losses, pay cuts and higher taxes. For some households with tracker loans – that is, mortgages where the interest rate tracks the ECB policy rate at a fixed premium – repayments have also fallen in line with ECB policy rates. Other households, either with fixed or non-tracker variable rate loans, have not benefited to the same degree. We use HFCS-SIM to highlight this disparity in interest rate pass through, and show how, in many cases, it falls along age lines - with older and less indebted households more likely to have low pass-through arrangements.

Figure 8 plots the evolution of debt, disposable income and mortgage debt repayments for three groups: households born during or after the 1970s (i.e., the oldest household in this group is 35 in 2005); households born in the 1960s; and households born before the 1960s. In all cases we restrict the analysis to households with property debt and nominal values are indexed to 2005=100. As expected, the youngest cohort (1970s onwards) have the sharpest increase in debt in the run-up to the crisis, with a 20% increase in debt levels between 2005 and 2008, more than twice the rate of income growth for this period. Older groups, and particularly the oldest group (the 1950s cohort) see relatively small increases by comparison, but also experience stronger income growth up to 2008.

Since 2009, and compared to younger borrowers (1970s cohort), older households have reduced their debt levels at a much faster rate, with debt falling by over 30% up to 2014. The main reason for this is the lower debt level and shorter mortgage terms for older borrowers, such that for a given repayment the reduction in debt (as opposed to repaying interest) is larger. As Table 4 shows, for HMR loans older borrowers have much shorter loan terms remaining, as expected.

Table 4: HMR mortgage debt characteristics, by birth cohort

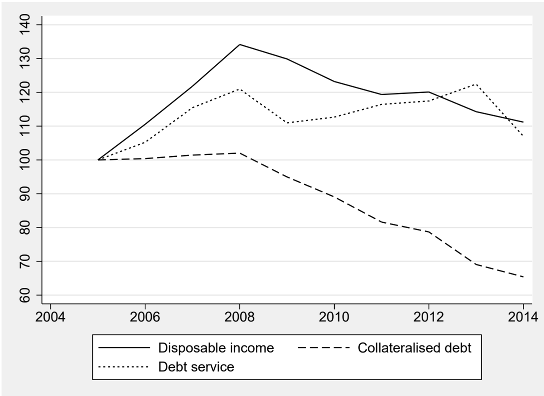
	Birth cohort			
	1950	1960	1970	All cohorts
Term remaining in 2013 (years)	7	13	23	17
Monthly repayment (€)	596	700	870	800
Outstanding debt (€)	48,351	98,089	174,000	129,000
Mortgage interest rate (%)	4.0	3.8	3.5	3.8
Tracker interest rate share (%)	20.0	29.5	39.2	32.9
Interest only share (%)	4.8	8.7	5.4	6.3
Extended mortgage term 2005-2013 (%)	12.8	18.5	14.0	15.2
Missed payments 2012/13 (%)	20.7%	22.8	15.4	18.6
Missed payment outstanding (2013) (%)	10.1	14.2	7.3	9.9

Source: HFCS-SIM (2017).

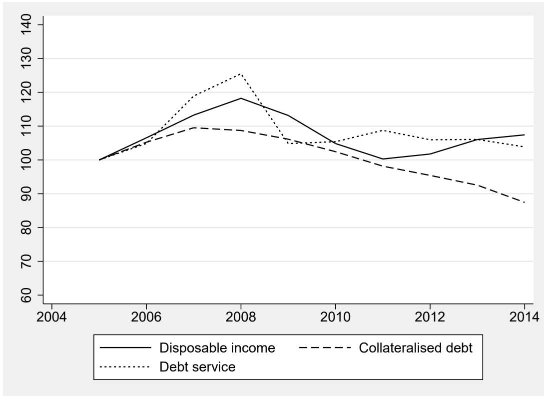
Whilst older cohorts have deleveraged the most relative to their peak debt position, it is younger households that have experienced the most significant reduction in their debt repayments. The sharp fall in ECB policy rates in 2008 and 2009 led to an almost 30% fall in the debt repayments for younger borrowers. Other birth cohorts also saw

Figure 8: Property debt and disposable income indices, by birth year cohort (median) or interest rate type

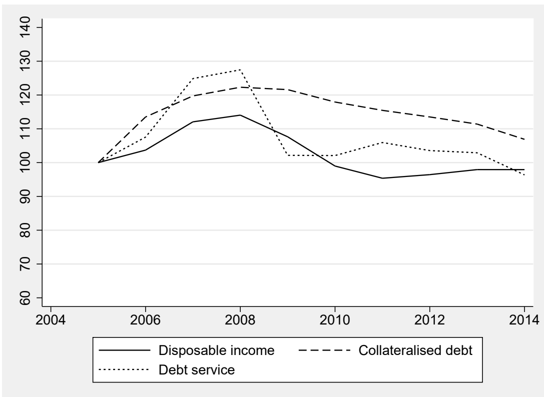
(a) Born in the 1950s and earlier



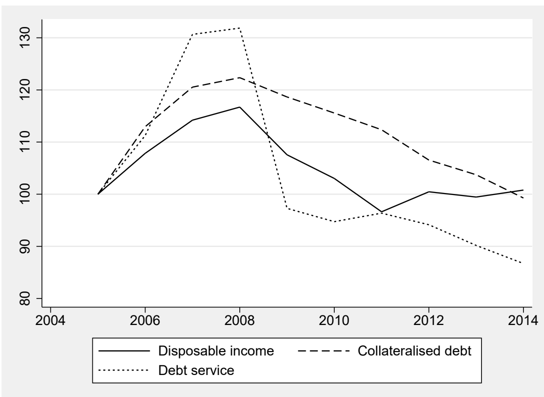
(b) Born in the 1960s



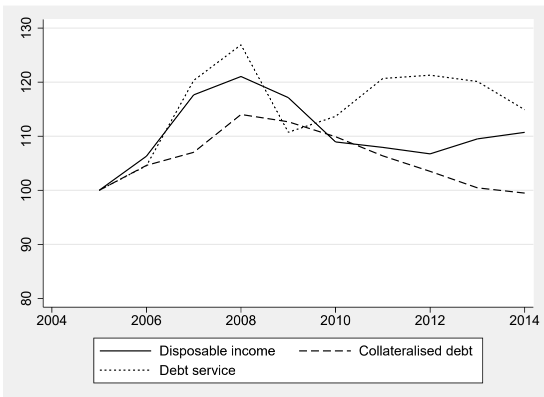
(c) Born in the 1970s and later



(d) Borrowers with a tracker mortgage



(e) Borrowers with an SVR mortgage

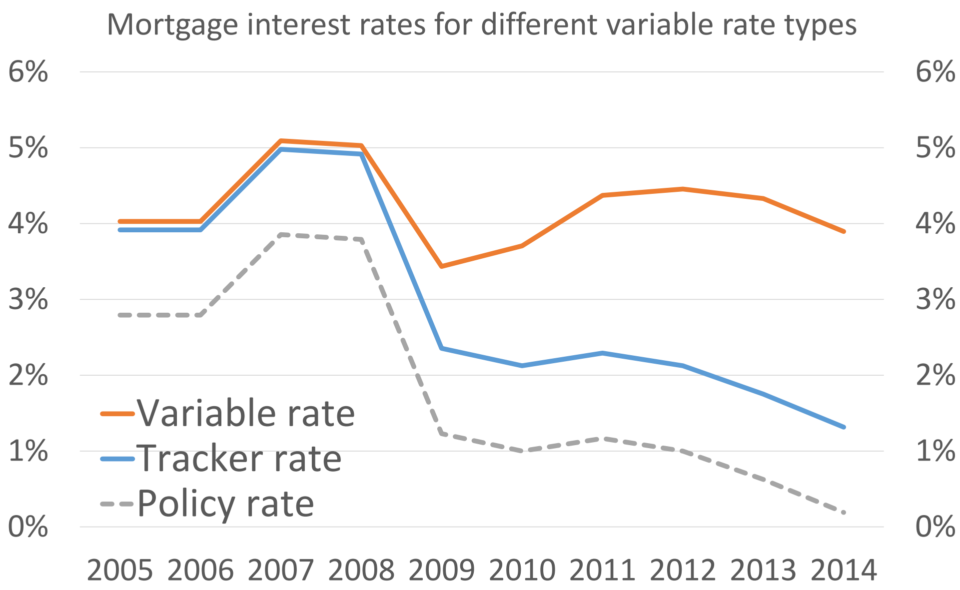


Source: HFCS-SIM (2017), conditional on having property debt.

their debt burden fall during this period, but not by nearly as much. Furthermore, *after* 2009 the debt service burden for the 1950s cohort actually rose gradually until 2013.

The reason older cohorts exhibit lower pass-through from changes in the ECB policy rate is that fewer of them are on tracker mortgages. As we show in Table 4, the share of trackers amongst younger borrowers is almost double that of the oldest borrowers. Goggin et al. (2012) show that from 2009 onwards crisis-hit Irish lenders changed their approach to setting rates for tracker versus other variable rate mortgage loans, with significantly higher rates for non-tracker variable rate loans after 2009. These differences are embedded in our approach to constructing HFCS-SIM, and therefore reflected in mortgage repayments (Figure 9). Figures 8d and 8e shed further light on the importance of interest rate type for the debt service burden during the crisis, redrawing the debt, income and debt-service trends from before, this time according to variable interest rate type (i.e. tracker or non-tracker). Despite larger declines in disposable income between 2008 and 2013 (15% versus 10%), when compared to other variable rate borrowers, those with tracker loans benefited from significantly larger payment reductions. In fact, by the end of our simulation period (2014), non-tracker variable rate borrowers' repayments are not too far below 2008 levels, despite the unprecedented drop in policy rates since then.

Figure 9: Mortgage interest rates 2008 and 2013, by interest rate type



Source: HFCS-SIM.
Note: Policy rate = ECB policy rate.

5 Debt repayments and income shocks

The scale of the income shock which hit Irish households after 2008 led to widespread mortgage repayment problems. Stressed households, with high debt repayments relative to their now lower income, reacted in a number of ways. Some reduced their payments by modifying loan repayment terms; for example, using term extensions and moving to IO repayments. Missed mortgage repayments also became increasingly common, with over one-quarter of loans in arrears by mid-2013.[10] We use the income time series in our dataset, combined with information on loan modifications and missed payments, to understand how highly indebted households responded to income shocks.

[10] Related to this, Le Blanc (2016) notes that, relative to their European counterparts, Irish households are almost twice as likely to leave bills unpaid in response to an income shock.

5.1 Mortgage modifications

As several papers show (Danne and McGuinness, 2016; McGuinness, 2014; Kelly et al., 2014), loan modifications were increasingly used by highly indebted households throughout the crisis. Mortgage arrears statistics published by the Central Bank of Ireland show that by early-2014 one out of every eight loans had been modified in some way. Around one-third of modified loans moved to IO or term extensions, meaning that when we exclude mortgages in arrears, where the modifications primarily consist of arrears capitalisation, more than half of modifications are IO or term extensions.

One crucial piece of information missing from the analysis of these arrangements to date is the scale of the income shock experienced by these households. As this is known in HFCS-SIM, in this section we compare the scale of the income shock, the debt service burden and other characteristics of borrowers that sought out loan modifications during the recession. We focus on modifications occuring between 2008 and 2013; that is, the period when incomes fell sharply. Between 2008 and 2013, approximately 200 households in the sample switched to IO or extended their loan term. We find very few cases (10%) of households receiving both types of modifications, consistent with the evidence in Danne and McGuinness (2016). Despite the relatively low number of observations, in percentage terms the share of modifications in the sample is very similar to that in the published statistics. Because we want to focus on modifications that reduce debt repayments, we exclude a very small number of term extensions which were part of a top-up loan. Tables 5 (interest-only, 'IO') and 6 (term extension) summarise the characteristics of households with and without HMR mortgage modifications. Households that availed of either an IO arrangement or term extension experienced much larger negative income shocks between 2008 and 2013. The difference is largest for the IO group where the median household experiences a drop of 24.3% compared to 11% for borrowers that did not switch to IO. The differential for term extension households, while relatively smaller (20% versus 11%) is still very large.

In both absolute terms and relative to their income, IO borrowers are more heavily indebted. The median debt to disposable income ratio for IO borrowers is 5.2, compared with a range of 2.5 to 3.1 for all other groups in the two Tables. The higher debt levels result partly from the fact that these borrowers have not made any principle repayments on their debt for several years. However, even accounting for this fact, IO borrowers would appear to be more indebted.

In terms of reducing the debt service burden, both Tables highlight the significant benefit to borrowers from modifying their loan terms. In 2013, the median IO borrower's monthly repayment was almost €160 lower than a principal plus interest repayment arrangement. This amounted to a six percentage point reduction in the debt service ratio (to disposable income), from 30% to 24%. The reduction in repayments for borrowers who extend their loan terms is slightly smaller at around €120 per month, representing a 4 percentage point reduction in the debt service ratio. This smaller reduction in repayments in the latter case is to be expected, given that repayments for borrowers who extend their mortgage term still contain some portion of amortisation over and above the interest payment.

Given all of the above, one obvious question is whether loan modifications, and the associated reduction in the debt service burden, reduces the likelihood of a borrower experiencing debt repayment problems. We examine this in more detail below.

5.2 Income shocks and missed mortgage distress

The analysis in this section builds on several recent papers which have used mico-data to understand how income shocks lead to debt distress; including Galuscak et al. (2014); Johansson and Persson (2006); Albacete and Fessler (2010). However, the key difference here is that whereas existing papers typically impose top-down shocks to incomes (e.g. an employment shock) or repayments (e.g. an interest rate shock) we relate missed payments to historic income shocks of HFCS households. Specifically, we quantify the extent to which current and lagged information on employment, income, house prices and repayments impacts on debt distress.

Table 5: Median characteristics of households that switch to interest-only payments

	Switch to interest-only 2008-13	
	No	Yes
Disposable income 2008 (€)	59,159	49,349
Disposable income 2013 (€)	52,740	32,084
Income change (%)	-11	-24.3
Mortgage balance 2013 (€)	134,700	168,000
Term remaining 2013 (years)	17	25
Mortgage interest rate 2013 (%)	3.7	3.9
Tracker mortgage share (%)	34.5	26.2
Principal & interest repayments (monthly, €)	825	809[a]
Interest only payments (monthly, €)	NA	650
Difference (%)	NA	-20
Full debt repayments/income (%)	19	30
Interest only payments/income (%)	NA	24
Age (median 2013)	43	44
Share with other (non-HMR) mortgage debt (%)	9.0	13.1

Source: HFCS-SIM (2017).

Notes: Sample is households with a HMR mortgage.

(a) This is what we estimate payments *would be* were full principal and interest payments being made.

Table 6: Median characteristics of households that extend their mortgage term

	Term extension 2008-13	
	No	Yes
Disposable income 2008 (€)	59,018	54,165
Disposable income 2013 (€)	52,484	43,473
Income change (%)	-11	-20.0
Mortgage balance 2013 (€)	135,925	135,350
Term remaining 2013 (years)	17	21
Term remaining *without* modification (years)	NA	16
Mortgage interest rate 2013 (%)	3.7	3.2
Tracker mortgage share (%)	33.5	44.6
Principal & interest repayments (monthly, before extension, €)	820	855
Principal & interest repayments (monthly, 2013, €)	820	731
Difference (%)	NA	-17
Debt repayments/income (before extension, %)	19	24
Debt repayments/income (2013, %)	19	20
Age (median 2013)	43	42
Share with other (non-HMR) mortgage debt (%)	9.4	5.5

Source: HFCS-SIM (2017).

Notes: Sample is households with a HMR mortgage.

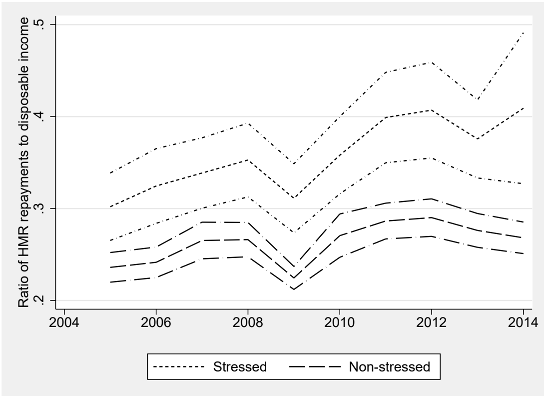
It is important to be aware that the information on mortgage repayment problems in the HFCS does not map directly to published mortgage *arrears* statistics, which tend to focus on 90-days past due – a standard default measure in the literature. Rather, HFCS households are asked in 2013 whether they have missed any mortgage repayments in the last twelve months, and whether missed payments are still outstanding. Around 19% of borrowers missed a mortgage payment in the previous 12 months, with just under half of these (9%) still outstanding. To keep the discussion manageable, we focus on the second measure – outstanding missed payments or arrears – although all the relationships that hold for outstanding arrears also hold for the other measure.

A large literature on the determinants of mortgage arrears has sought to disentangle the effects of equity considerations versus repayment problems as the key drivers of arrears trends.[11] Figure 10 compares trends in average repayment ratios and outstanding loan to value (LTV) ratios for households that have missed a mortgage repayment ('stressed' borrowers) versus those that have not ('non-stressed' borrowers). The most obvious difference is that households that miss a mortgage repayment have a significantly higher repayment burden (Figure 10a) – some 9 percentage points higher *on average*. This is an important result as it suggests that the amount of *ex-ante* financial 'headroom' a household has is an important factor in determining their ability to cope with repayment shocks. There is also some evidence to suggest that the repayment burden for stressed households deteriorated marginally throughout the recession, whilst that of non-stressed households remained broadly stable.

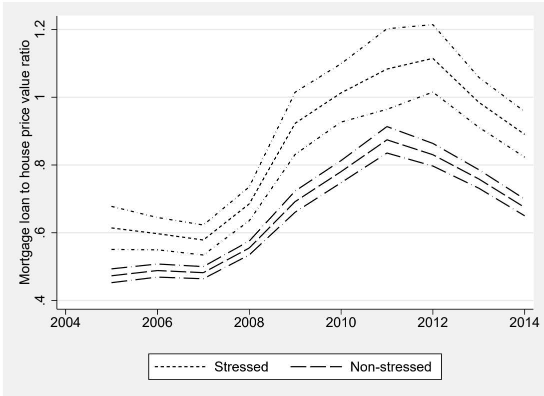
[11] See Lydon and McCarthy (2013) and McCarthy (2014) for a comprehensive review of this literature in the Irish context.

Figure 10: Mortgage arrears in the HFCS

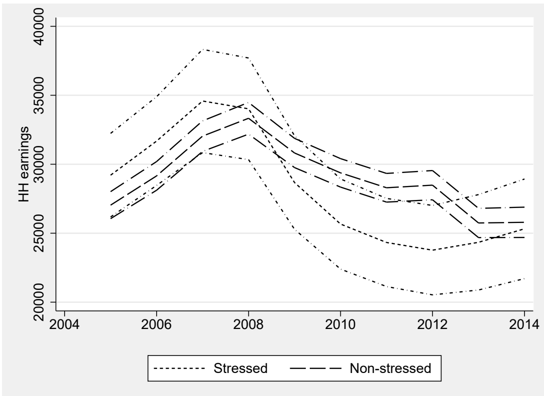
(a) Repayment ratio, mean



(b) LTV, mean



(c) Disposable income, mean



Source: HFCS-SIM (2017).
Note: Dotted line is 95% Confidence Interval.

The LTV trends for stressed and non-stressed borrowers follow a broadly similar pattern (Figure 10b). However, in the last few years of the simulation period (2011 onwards), the non-stressed group managed to reduce their LTV by more. The confidence intervals for the stressed group are quite wide at the peak (2010/11) however they narrow from 2012 onwards, suggesting that the difference is statistically significant.

The income trends for stressed and non-stressed borrowers follow a more complex pattern, with wider confidence intervals for the stressed borrower in particular making inference more challenging (Figure 10c). While both groups experienced rapid income growth up to 2008, stressed borrowers saw larger income declines although these attenuated earlier than for non-stressed borrowers, with income levels for the former appearing to recover more quickly than those of the latter. More generally, stressed and non-stressed households in the HFCS have vastly different income and employment histories: 23% of stressed borrowers lost their jobs between 2007 and 2012, compared to just 7% for non-stressed borrowers.

5.2.1 Empirical results

We quantify the relationship between income shocks and mortgage distress by examining the marginal effects from a probit model where outstanding missed payments ('arrears') is the dependent variable (see Table 7).[12] As expected, households that experienced a large negative income shock between 2008 and 2013 are significantly more likely to be in arrears on their mortgage repayment (Table 7, column 1). However, income shocks need to be quite significant (-10% or lower) before these effects kick in.[13] For households that experienced at least a 10% income drop, the likelihood of being in arrears is increased by between 4.4% and 6.6%. These are large effects when we consider that the sample mean is 9%. Other variables such as marital status (dummy variable where divorced = 1), employment experience (dummy variable where job loss 1 1 and unemployment duration) are included to capture possible negative income shocks. The marginal effects for these variables (around 7%) are highly statistically significant. Finally, we also include the gross liquid assets to income ratio (in 2013) as a potential buffer against income shocks.[14] The ratio appears to play an important role: controlling for income shocks during the 2008 to 2013 period, households with more savings are significantly less likely to be in arrears. The median for this ratio is 0.10 – i.e. the median household in 2013 had gross savings equal to around 10% of disposable income – and the 90$^{\text{th}}$ percentile is 0.90. The marginal effects from the probit suggest that, accounting for income shocks, households in the latter group are around 6% *less* likely to be in arrears.

[12] Here we draw on the extensive literature on the determinants of mortgage arrears; see, for example, Aron and Meullbauer (2010, 2011) and Central Bank of Ireland (2012).
[13] Note, to allow for non-linear effects, we include income shocks in piece-wise form.
[14] Gross liquid assets are defined in Lawless et al. (2015) as being equal to financial assets plus net business wealth.

In the second column in Table 7 we restrict the estimation to households that entered the recession with an already high-debt service burden. We define this group to be the top quartile of the mortgage debt repayment to disposable income ratio in 2008; the threshold is 0.27 and above (the median (mean) debt-service burden in 2008 *within* this group is 0.35 (0.48)). The reason we look at this subgroup is that ex-ante, and from the summary statistics in particular, we have a strong prior that income shocks matter more when the debt-service burden is higher. This is exactly what we find: the marginal effects on the income shock variable almost double (but the income shocks still need to be large, i.e. $>$-10%). The job loss and unemployment duration effects have also doubled in size. This is an important result for *macroprudential* policy, as it suggests that policies aimed at reducing the number of households in the right-hand tail of the debt-service distribution can have very positive implications for the ability of indebted households to withstand negative income shocks.

Table 7: Probit: Dependent variable is missed mortgage repayments

	(1) All mortgaged households	(2) High debt-service households
Δ Income 2008-13		
0 to +20%	0.0199	0.0256
	(0.0200)	(0.0379)
-10% to 0	0.00728	-0.00172
	(0.0188)	(0.0348)
-20% to -10%	0.0443**	0.105**
	(0.0215)	(0.0451)
$\geq$-20%	0.0665***	0.0946**
	(0.0195)	(0.0381)
Divorced	0.0756***	0.130***
	(0.0202)	(0.0383)
Lost job (2011/12)	0.0713***	0.123***
	(0.0204)	(0.0397)
Unemployment duration (years)	0.00659***	0.0130***
	(0.00146)	(0.00351)
Gross liquid assets/income	-0.0757***	-0.0832**
	(0.0210)	(0.0399)
Negative equity (2013)	0.0894***	0.0829***
	(0.0151)	(0.0295)
Age	0.0129**	0.0171
	(0.00581)	(0.0115)
Age^2	-0.000111*	-0.000156
	(0.0000608)	(0.000124)
Observations	1,671	548
Missed mortgage repayments (%)	8.9	13.6

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. High debt service households are those in the top quartile of the 2008 debt-service distribution, i.e. $\geq$ 27% of disposable income goes to mortgage repayments.

6 Conclusion

This paper presents a methodology for 'aging' household-level information on asset values, debt and incomes in the 2013 Irish HFCS. Using a combination of micro and macro data we re-construct the balance sheets of over 5,000 households from 2005-2014. We show that for a wide range of balance sheet components the estimated balance sheets *in aggregate* track actual aggregate databases closely. We are most confident of the simulation techniques applied to property-related assets and debts as well as employment income. These constitute the vast majority of asset holdings (78% in aggregate; 87% at the median), outstanding debts (94% in aggregate; 87% at the median contingent on holding debt) and income received by most households. The applications in the paper are focused on these elements of the simulated data.

This exercise provides some key insights into how different households were affected by the recession, both in terms of shocks to their incomes and asset price declines. Net wealth to disposable income ratios have declined sharply from their 2007 peak. Older age groups (aged 65 and above in 2013) suffered the largest losses, falling from a peak (median) value above 11 in 2007 to just above 8 in 2013. The high concentration of gross wealth in property assets – both the home they live in and other property – drives this result. In terms of the level of wealth, the euro-value losses are heavily concentrated in the bottom end of the wealth distribution. These are mainly young households, who, having bought property closer to the peak of the boom, started out with low net wealth positions – the median net wealth for households in the bottom quintile in 2006 is €1,700. The fall in property prices drives these households into a negative equity position by 2013, with net wealth holdings of *minus* €31,000.

The HFCS-SIM dataset also gives a sense of how leverage, measured as the debt to disposable income ratio, has evolved over time. Commentators often cite the dramatic decline in *aggregate* debt as an indicator that households have been deleveraging in recent years. Figure 5 does show large falls in average HMR mortgage debt from €190,000 in 2007 to €160,000 by 2013. However, once we take account of the falls in income in the same period, and the differences in the rate of amortisation for certain groups, a very different picture emerges. Younger households – those aged between 18 and 44 in 2013 – saw large increases in their leverage ratios from 2006 through to 2010 rising by around 75 percentage points, largely as a result of falls in disposable income for these groups. Furthermore, these households have experienced relatively minor declines in leverage ratios since 2010, both as a result of weak/no disposable income growth and the slow amortisation rates arising from long mortgage terms and very high debt levels. The widespread use of mortgage modifications among this group, notably the use of mortgage extensions, also plays a significant role in slowing the rate of mortgage debt repayment. However, the prevalence of tracker mortgages in these younger cohorts saw the debt service levels of the 1970s cohort, and particularly the cohort born in the early 1980s, decline more quickly than their incomes from 2008 on, providing some amelioration of the effects of the income shock on debt repayment in these cohorts. Other households, either with fixed or non-tracker variable rate loans, have not benefited to the same degree. This effect of the low interest rate environment (for highly leveraged borrowers) is of policy interest and warrants more attention in future work.

In a second application of HFCS-SIM we examine the factors associated with mortgage repayment problems. We define stressed households as those with high debt repayments relative to their incomes and examine the incidence of mortgage modification as well as missed mortgage payments for stressed and non-stressed households. Accounting for income shocks is crucial when examining mortgage modifications. In relation to missed mortgage payments, we show that affordability plays a key role, through income levels, employment shocks and debt-service ratios. Households that have built up a financial buffer are, not surprisingly, less likely to miss a payment, controlling for shocks to income levels. Finally, households in negative equity are more likely to miss a payment, all other factors held constant. We associate positive changes in some of these factors with the decline in mortgage arrears observed in recent years.

The applicability of the results here to a non-Irish context depend heavily on comparability between institutionally similar environments elsewhere. Examination of some of the issues described above in other HFCS countries will be of interest now that HFCS Wave 2 data are available. This paper highlights, once again, the importance of accounting for distributional effects when examining wealth, leverage and debt distress from a policy perspective.

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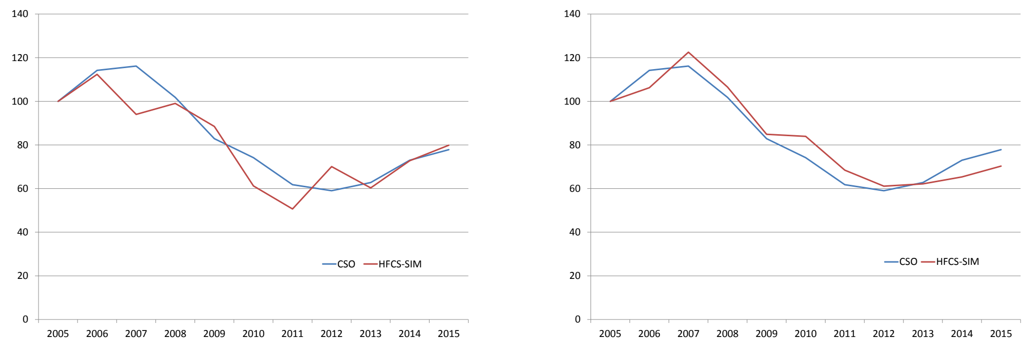
A Data Appendix

A.1 Simulation validation

Figure A1: House price indices CSO (2006=100) and simulated HFCS

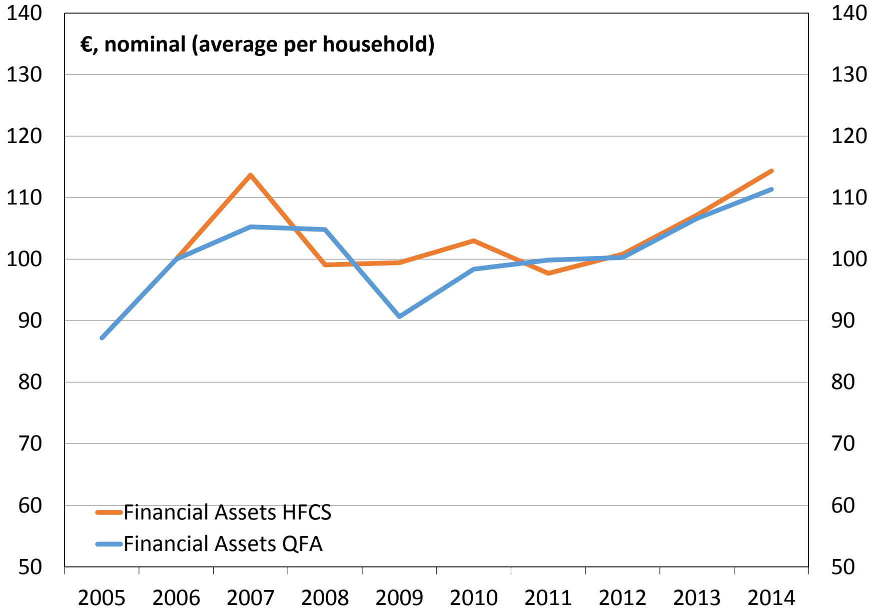
(a) All property types, Dublin

(b) All property types, non-Dublin



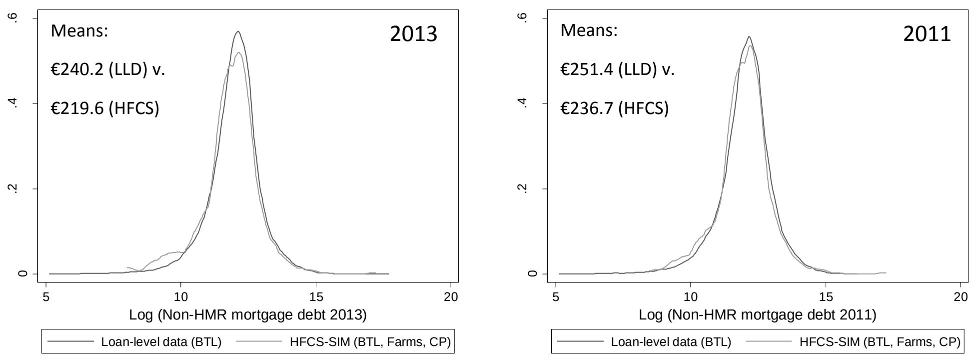
Source: HFCS-SIM (2017) and RPPI (CSO, 2016) .

Figure A2: Average value of financial assets: QFA *versus* HFCS-SIM (2006 = 100)



Source: Central Bank of Ireland for QFA, and HFCS 2013

Figure A3: Non-HMR mortgages in HFCS-SIM (BTL and Comm. Prop.) and LLD (BTL only)



Source: CBI LLD (2016); and HFCS-SIM (2016).