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Administrative meets survey data: measuring household indebtedness in Ireland

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Non-Technical Summary

Surveys, such as the Household Finance and Consumption Survey (HFCS), are a crucial source of microdata on household finances. Providing granular information on the composition of household balance sheets and the distribution of wealth, they also enable microsimulations, stress tests and other scenario analysis. These exercises are essential in helping central banks and other policymakers to consider the impact of policies and better understand transmission mechanisms. However, as surveys are reliant on respondents self-reporting accurately, they can suffer from misreporting, whether intentional or not.

One solution to overcome this problem is to incorporate more administrative data into surveys. This data reflects detailed information that is collected by government departments, agencies or other organisations for their own purposes. The Central Bank of Ireland's Central Credit Register (CCR) is one example. It contains personal and credit information on all types of consumer loans of €500 or more, collected under the Credit Reporting Act 2013 to improve the understanding of lending patterns by both the Central Bank of Ireland and lending institutions in Ireland.

Data from the CCR was incorporated into Ireland's HFCS for the first time in 2020. As a result, the 2020 HFCS shows a large increase in both debt participation and total outstanding balance compared to the last wave, collected in 2018. The purpose of this paper is to estimate the extent to which these increases are due to the CCR revealing debt which households previously omitted or under-reported, and then explore the implications of this for our understanding of overall household indebtedness in Ireland.

To do this, we analyse the debt information of panel households who completed the survey in both 2018 and 2020. Specifically, we look at their main residence mortgage debt, non-collateralised loans and credit cards, and estimate the extent to which these debts constitute "new" borrowing; an "existing" balance carried forward from 2018, or debt which has been "revealed" by the CCR. We also consider whether the CCR has improved the accuracy of details surrounding debts, such as loan origination year or initial amount borrowed, and explore who in the Irish population holds revealed debt.

We provide evidence that the CCR has corrected initial under-reporting. At a minimum, almost one in three households hold some revealed debt and we estimate that this contributed to around half of the net change in debt participation observed since the last HFCS. The increase is driven principally by credit card debt, which has the highest share of revealed debt holders. Interestingly, we show that households with more complex balance sheets are more likely to benefit from the inclusion of the CCR; with not just quantity, but also variety of items, an important predictor of holding revealed debt.

Securing an accurate view of the overall indebtedness of the household sector is particularly important for Ireland, in light of the elevated debt levels experienced after the Global Financial Crisis. Our results illustrate the value of incorporating administrative data into household finance surveys and add to the economic measurement literature by demonstrating how a simple approach applied to panel data can be used to estimate measurement error.

Administrative meets survey data: measuring household indebtedness in Ireland

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Abstract

The 2020 Household Finance and Consumption Survey (HFCS) marked the first time that survey data from Irish households was supplemented with administrative data from the Central Bank's Central Credit Register (CCR). Using household level data from the panel component of the survey, weighted to the full population in 2018, we develop a simple approach for estimating measurement error and applying it, find at least one third of households hold "revealed debt" worth almost 13 per cent of the value of total debt outstanding in 2020. In doing so, we show that incorporating the CCR into the HFCS has helped to correct for under-reporting and improved the overall quality of liabilities data in the survey. Controlling for demographic and income characteristics, we find that households with more complex balance sheets are more likely to hold revealed debt. The results suggest that incorporating administrative data into surveys can help alleviate issues surrounding recall bias and other human errors that may generate initial misreporting.

JEL classification: G51, D1, D0, G0.

Keywords: household finance, debt, borrowing, balance sheet, economic measurement, surveys, admin data.

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1 Introduction

The Household Finance and Consumption Survey (HFCS) is the most comprehensive survey source of household debt information in Ireland. As part of a Eurosystem project coordinated by the ECB, the HFCS gathers granular and comparable information on household balance sheets – including households' mortgage and non-mortgage debt – across the euro area. Three waves of data, collected in 2013, 2018 and 2020 by the Central Statistics Office (CSO), are available for Ireland.[1]

In the earlier 2013 and 2018 waves, the survey respondent for a given household was asked to self-report the outstanding balance and other characteristics (such as the initial amount borrowed, loan length and current interest rate) about the household's debts. However, from the 2020 wave onwards, the CSO was able to supplement these self-reported responses with administrative data from the Central Credit Register (CCR).

The CCR is a centralised database that collects and securely stores personal and credit information on all types of consumer loans of €500 or more. This includes mortgages, credit cards, overdrafts, hire purchases and personal loans. The CCR data is collected at an individual level by lending institutions and submitted to the Central Bank of Ireland. Using name, gender and date of birth, HFCS respondents can be matched with their corresponding CCR data, with the CSO then able to aggregate the debt information to the household level.

The inclusion of the CCR is a significant development. Recalling the specificities of every debt for every household member is a difficult task. Errors can understandably occur leading to a gap between aggregate debt statistics at the macro level and the value of debt estimated using weighted, micro level data from the HFCS. With the survey data for 2020 onwards enhanced by populating household responses to certain debt questions with register data from lenders, the gap can be closed.

As a result, the accuracy of debt coverage in Ireland has greatly improved. Comparing HFCS 2020 (which includes the CCR) with HFCS 2018 (which excludes the CCR), debt participation rose 16.3 percentage points and outstanding balance by €10.1bn. To understand the drivers of this change, we use the panel component of the HFCS and focusing on households' main residence (HMR) mortgage debt, non-collateralised loans (NCLs) and credit cards, measure how much of each debt is "new", "existing" or has been "revealed" by the CCR. In doing so, we demonstrate the value of incorporating administrative data into household finance surveys and make an important contribution to the economic measurement literature by illustrating how a simple approach can be used to estimate the bias that has been corrected.

Our analysis indicates that, at a minimum, one third of households hold revealed debt, rising to 47.6 per cent if we condition only on debt holders. The extent of initial measurement error is found to vary by debt type and is largest for credit card debt. The value of revealed debt is equivalent to around 13 per cent of the total debt outstanding in

[1] The official ECB HFCS release refers to wave 3 as "HFCS 2017" and wave 4 as "HFCS 2021". However, as this paper only focuses on Ireland, we refer to "HFCS 2018" and "HFCS 2020" instead as this more accurately reflects when the Irish data was collected; between April 2018 to early January 2019 for wave 3 and between July 2020 and January 2021 for wave 4.

2020, and we estimate that this contributed close to half of the net change in aggregate debt participation observed between waves.

This revealed debt has important implications for our understanding of indebtedness in the household sector. Had it not been identified, the debt participation rate would have remained at around half of households (as opposed to its true figure of over two thirds) and financial fragility measures would have recorded weaker improvements between waves. Improved accuracy of HFCS debt information provides other benefits. We show that the CCR has also improved the accuracy of the characteristics of individual debts. This supports more accurate calculation of monthly debt payments and in turn, enables improved simulation analysis of the distributional implications of debt or interest rate changes on economic variables (see Arrigoni, Boyd and McIndoe-Calder (2022) for an example of such scenario analysis performed by the Central Bank of Ireland). Establishing the correct level of debt in an economy also means a more accurate view of net wealth and how it is distributed amongst households. In an Irish context, this is especially important given the elevated debt levels experienced by households following the Global Financial Crisis (GFC).

We show that households with more complex balance sheets are also more likely to benefit from the inclusion of the CCR, with diversity seemingly more important than quantity. Each additional type of debt on a household's balance sheet increases the probability of holding revealed debt by 1.7 times that of a simple increase in number of debts. The findings suggest that administrative data can help to correct for recall bias and other human errors that self-reported responses are vulnerable to.

The remainder of this paper is structured as follows. Section 2 motivates the analysis by detailing the change in debt participation observed since the last HFCS. Section 3 explains our approach to identifying the debt revealed by the CCR and how we will evaluate its impact on debt coverage and data quality. Section 4 presents the results of our approach applied to HMR mortgage, NCL and credit card debt. Section 5 explores the household characteristics of revealed debt holders. Section 6 considers the aggregate implications of our results including for financial fragility. Finally, Section 7 concludes.

2 Motivation

Economists and policymakers increasingly rely upon survey data for understanding the finances of households and exploring the distributional implications of policies and shocks. Yet their dependence on accurate self-reporting by respondents can mean survey data suffers from misreporting, whether intentional or not.

The problem of misreporting debt information in the HFCS can be separated into two issues. The first is “item non-response”, whereby a household omits to report holding a debt. This problem is potentially greater for household surveys, where the respondent may be providing a proxy response from an incomplete knowledge set. The second issue is “measurement error”, whereby a household provides an inaccurate answer, such as an outstanding balance that is either too low or too high. This constitutes a non-sampling error, which adds noise to the data and can pose a large problem for household surveys (D'Alessio, 2020).

There are many reasons why households may misreport. These include a lack of knowledge or awareness; diminished memory of retrospective events; rounding; deliberate omission or under-reporting because of fear of being defrauded or facing legal and tax implications or alternatively, a desire to socially conform or impress the interviewer (Neri et al., 2012).

The rational inattention literature (revolving around the idea that economic agents cannot absorb all information available to them but can choose what to select, summarise and internalise) suggests that misreporting in surveys could be driven by the costs associated with a household updating their information set exceeding the benefits (Maćkowiak et al., 2021; Reis, 2006 and Sims, 2003).

In exploring how well US mortgage holders report their mortgage characteristics, Bucks and Pence (2008) use the rational inattention framework to propose four possible explanations for why they find that some variable rate borrowers misunderstand the extent to which the interest rate on their mortgage could change. Firstly, the benefits of acquiring and maintaining this knowledge might be small if interest rate changes would have only a minor effect on borrower finances. Secondly (and the explanation they find most convincing), it may be costly for borrowers to acquire or mentally process this information. They also hypothesise that the misunderstanding is due to optimism bias (leading to borrowers believing it unlikely they will experience financial misfortune) and present bias (leading to borrowers being more focused on their immediate payments than changes to the future flow).

In the context of the HFCS, "costs" might be thought of as the time required to source the loan documents and compile the detailed information of all debts held by all household members. There is then the cost of a longer time to complete the questionnaire and the household respondent may experience a reduction in utility from time spent away from leisure or more preferred pursuits. If a household is content with the level of their current debt payments, they may feel less need to pay close attention to the current status of their debts or re-check their terms ahead of an HFCS interview. Alternatively, if there are concerns about the households' debt levels, a household may perceive the costs of updating – and thereby acknowledging – these concerns as large and exceeding the short-term benefits of remaining unaware.

The literature to date has highlighted the widespread problem of misreporting. Studies such as Bollinger et al. (2018) find the problem of missing earnings data is not random. The tendency for survey respondents to misreport income, particularly self-employment (Hurst et al., 2014; Cabral et al., 2019) transfers (Meyer et al., 2015) and capital income has been noted, with the latter likely related to difficulties in surveying the top of the distribution (Ooms et al., 2021). Aside from earnings, evidence also suggests that financial assets – particularly shares, mutual funds, deposits and savings – are measured with lower precision (D'Aurizio et al., 2006; Biancotti et al., 2008).

Several studies in the economic measurement literature have previously explored the correspondence in debt information between survey and administrative data. The aforementioned Bucks and Pence (2008) compared borrower reported debt information from the US Survey of Consumer Finances (SCF) to lender reported data from the Loan Performance Corporation and the Residential Finance Survey. They conclude that borrowers appear to know the basic terms of their mortgages but there is evidence that those with variable rate mortgages appear to underestimate or not know the extent to which their interest rate could change.

Johnson and Li (2009) similarly compare the debt information of the SCF (this time treating it as the most accurate source in part because of the conclusion of Bucks and Pence, 2008) to the debt information provided by the Consumer Expenditure Study (CES). While, a close match is found for vehicle and credit card debt, they conclude that the CES under-reports mortgage debt.

In contrast, Zinman's (2009) comparison of the SCF against the lender reported Consumer Credit G.19 data, finds households underreport credit card debt by a factor of two. Likewise, in comparing SCF derived debt levels against lender reported levels from the FRBNY Consumer Credit Panel/Equifax (CCP), Brown et al., (2015) finds that while overall levels are similar, there are key exceptions with unsecured debt, namely credit card and student loans.

In an Irish context, Cussen, Lydon and O'Sullivan (2018) find loans reported in the Quarterly Financial Accounts (a statistical data source) to be roughly 1.3 times larger than in HFCS data.[2] One of the key reasons for incorporating administrative data from the CCR into the HFCS was to address this "micro-macro" gap. Comparing the 2018 and 2020 HFCS debt statistics, a substantial increase in debt participation across several debt types is observed, suggesting the inclusion of administrative data has been successful in closing the gap.

Specifically, between the 2018 and 2020 waves in Ireland, the HFCS indicates that participation in all debt types, with the exception of other property, overdraft and private loan debt, increased substantially (Table 1). For example, 30.4 per cent of households had HMR mortgage debt in 2020, up from 26.1 per cent in 2018. Participation in NCLs rose by over 15 percentage points (pp) to 43.9 per cent of households in 2020. However, the largest proportionate change was in the participation of credit card debt, which more than doubled from 12.7 per cent of households in 2018 to 26.8 per cent in 2020.

These increases occurred right across the income distribution (Figure 1). With regards to holding any debt, the greatest percentage point increase was observed for the second (+23.4pp) and third (+20.7pp) income quintiles. For HMR mortgage debt, the largest growth was amongst households in the top quintile (+10.1pp). However, changes in non-mortgage debt are most noteworthy. Between 2018 and 2020, participation in credit card debt increased by between 7.9pp in the first quintile to 17.0pp in the top quintile. While, participation in NCLs rose in the range of 7.2pp (first quintile) and 20.0pp (third quintile).

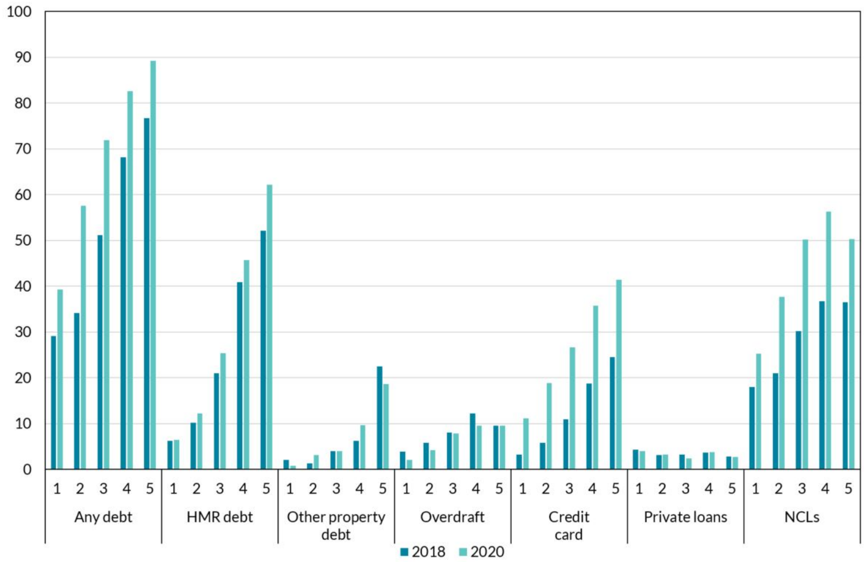
[2] Antoniewicz (2000) provides another example of liabilities information from survey data being compared with a statistical source.

Table 1. Share of households participating in different debt types, 2018 and 2020 (%)

	2018	2020	Percentage point (pp) difference	Percent change (%)
Any debt	51.8	68.1	16.3	31.4
Any HMR debt	26.1	30.4	4.3	16.5
Any other property debt	7.2	7.2	-	0.1
Any overdraft debt	7.9	6.7	-1.2	-15.8
Any credit card debt	12.7	26.8	14.1	111.4
Any private loan debt	3.5	3.2	-0.2	-7.0
Any NCL debt	28.5	43.9	15.4	54.2

Source: HFCS full sample (weighted to respective populations) and authors' own calculations.

Figure 1: Participation in debt, % by income quintile



Source: HFCS full sample (weighted to respective populations) and author's own calculations.
Note: Results based on full samples of 4,793 (6,020) households in 2018 (2020). Distribution reflects gross household income.

As a result of this increased participation, the total outstanding balance of debt increased by just under 9 per cent between 2018 and 2020, with HMR mortgage debt up €3.7bn and NCL debt by €1.6bn. These are substantial increases, particularly in non-mortgage debt given aggregate data indicates the outstanding balance for this debt type fell over the same period (Table 2).

Together, this suggests that the increase exhibited in the HFCS data is the result of the CCR more accurately capturing debt as opposed to new borrowing. It is the objective of this paper to confirm this and explore the implications of such a change, in both level and trend, for our understanding of household indebtedness.

Table 2. Outstanding balance between HFCS and aggregate statistics (€ bn)

	2018	2020	Change (€ bn) 2018-2020
	(HFCS excl. CCR)	*(HFCS incl. CCR)*	
HFCS ‡			
HMR mortgage debt	83.1	86.8	3.7
NCL debt	9.0	10.5	1.6
Credit & Banking Statistics †			
Principal dwelling loans	65.3	67.2	1.9
Personal lending	13.8	12.1	-1.7

Source:
‡ CSO - HFCS full sample (weighted to their respective populations). 2018 HFCS data is exclusive of the CCR. 2020 HFCS data is inclusive of the CCR.
† Central Bank of Ireland - Credit and Banking Statistics – Table A.18.1 Credit Advanced to Irish households from resident credit institutions and Table A.5.1 Loans to Irish household.
Table A.18.1 comprises licensed banks, building societies and, since January 2009, credit unions as regulated by the Registrar of Credit Unions (but excludes non-bank lenders). Personal lending reflects lending to private individuals in the form of consumer credit for the purpose of personal use in the consumption of goods and services only. It excludes lending for investment or business purposes, debt consolidation or education. All figures as at December of reference year. Any discrepancies are the result of rounding.

3 Data and Methodology

By and large, the methodology of the existing studies rests on distribution-level comparisons or comparisons of ownership rates and aggregate debt levels of the two data sources accompanied by difference of means tests. However, this approach poses several comparability challenges such as differences in weighting, sampling and definitions between the two sources and, as noted by Bucks and Pence (2008), survey and administrative distributions may still match despite offsetting errors in borrower data. Our study therefore makes an important contribution to the economic measurement literature as we are able to compare directly at the household level.

Like the case studies before, we also make the primary assumption that administrative data is more accurate than survey data and think of the difference between the two as representing measurement error.[3] In our study, we re-phrase this concept and use the term "revealed debt" to refer to debt which has been brought to light by the inclusion of the CCR.

The ideal approach for identifying revealed debt would be to directly compare survey responses against administrative data, with the gap between the two sources constituting revealed debt. Unfortunately, while close, this is not quite possible in our case due to our comparison having a time dimension. Specifically, we have survey data for 2018 and administrative data for 2020.[4] To overcome this deficit, we develop a simple strategy for identification which exploits the panel component of the HFCS. To the best of our knowledge, this paper represents the first to leverage the Irish HFCS panel.

[3]Bucks and Pence (2008) note this could be considered a strong assumption as administrative data can also be subject to processing errors or differences in question wording and interpretation which may produce inaccuracies.

[4]At the time of publishing this paper, the HFCS data for 2018 had been revised to include the CCR. However, as this revision required overwriting the original (pre-CCR) data for 2018, it is still not possible to directly compare the two waves in order to identify the exact amount of revealed debt. A panel data approach therefore remains the best way to try to estimate the likely impact of the CCR's inclusion.

3.1 HFCS panel data

The HFCS panel contains households followed in both 2018 and 2020, meaning their debt portfolio has been tracked over time. This helps us to identify revealed debt while at the same time, account for genuine, new borrowing and debt repayment.[5] Further, as the same households are surveyed, they should also have similar characteristics in both waves. This reduces the possibility that any change in their debt participation is related to household changes.

In using the panel data, some methodological points should be noted. Longitudinal weights for the HFCS are not yet available. Therefore, we adjust the cross-sectional weights in 2018 based on the gender, age, income and debt participation characteristics of the panel, and apply these to both waves.[6] We use the 2018 wave as our base as it is common practice to use the earliest wave.

Generally, we find the panel performs well against the full sample, particularly for participation. Nevertheless, there are some differences between our weighted panel and the weighted full sample. In particular, households in the panel have higher median income and net wealth in 2018. Panel households were also more likely to participate in debt in the last wave and are more likely to be home owners and have more complex balance sheets than the full sample. As a result, the level of the total outstanding balance of debt in 2020 is notably higher in the panel than the full sample. Therefore, caution is advised in interpreting aggregate debt balances in 2020 using the panel. While we link to the aggregate to motivate the usefulness of the CCR, our results are not intended to replace aggregate statistics. The panel also shows median HMR mortgage debt as being largely unchanged between waves whereas the full sample indicates a small decline. Alternate panel weight construction may have improved representation of some characteristics but at the cost of others. See Tables A.1 and A.2 in the Appendix for a detailed comparison of 2018 and 2020 debt and socio-demographic descriptives for the full sample versus the panel.

The remainder of this section sets out our approach to identifying “revealed" debt using the panel. This is followed by explaining how we evaluate the impact of the CCR in enhancing both the accuracy of debt *coverage* and *quality* of debt information.

3.2 Identifying revealed debt

We focus our analysis on HMR mortgages, NCLs and credit card debt as these are the debt types where full sample data indicates participation rose significantly. Taking each in turn, we categorise whether each panel household holds “existing”, “new” or “revealed” debt, or some combination of the three, in accordance with the definitions in Table 3.

[5] Panel households provide 2,808 observations, equivalent to 47 per cent of the 2020 sample and 59 per cent of the 2018 sample. Throughout our analysis, we use all 5 implicates available in the data. These are repeated observations of each household containing imputed values of certain variables, where data is missing.

[6] Specifically, we assign households into one of 100 groups based on their gender, age, income and debt participation characteristics. For each of these groups, we generate a weighting factor (which reflects the share of households in the total sample vs. panel sample). We then multiply the 2018 cross-sectional weights of the panel households with this weighting factor before re-scaling the weights to the size of the 2018 total population. These final weights are applied to both 2018 and 2020 wave panellists.

Table 3. Debt categorisation for HMR mortgages, NCLs and credit cards

	HMR Mortgages	NCLs	Credit Cards
Existing	Household has HMR mortgage debt which has been carried forward from 2018 to 2020	Household has NCL debt which has been carried forward from 2018 to 2020	Household is an existing card holder AND holds an outstanding balance in 2020 which is less than or equal to the balance held in 2018
New	Household took out an HMR mortgage for the first time in 2018, 2019 or 2020; OR has experienced an increase in debt balance that was likely due to refinancing since the last wave	Household took out an NCL in 2019 or 2020; OR household took out a loan in 2018 AND was previously a non-participant[7]	Household is a new credit card holder (i.e. holds a credit card in 2020 but did not in 2018) AND had applied for credit in the past three years[8]
Revealed	Household has an HMR mortgage recorded in wave 4 for the first time but the debt originates from before 2018; OR household has experienced an increase in balance which is likely not the result of refinancing	Household has experienced an increase in outstanding balance which is not the result of new debt	Household is a new credit card holder but did not apply for credit in the past three years; OR is an existing card holder AND experienced an increase in outstanding balance

Some points should be noted:

1. **The approach focuses on nominal balances, not number of loans.** This is because a household may have provided a single balance in wave 3 which combined multiple loans. If this is the case, then an increase in loans in wave 4 might not reflect additional debt but instead, the CCR helping reveal the true composition of debt.

2. **The definitions vary by debt type**. This is due to having more limited information for some types of debt. Specifically, originating year is the key variable for determining if a debt in 2020 should have been captured by the earlier HFCS wave. This information is available in both waves for HMR mortgages, but only in 2020 for NCLs and not at all for credit card debt.

3. **The approach does not amortise when accounting for debt repayment.** Instead, the value of debt repaid is just the difference between the value of a household's existing debt in wave 4 and their total outstanding balance in wave 3.[9] This was preferred as amortising based on the earlier wave was likely to produce significant inaccuracies.[10]

[7] As it is possible that a loan dated as originating in 2018 could be an existing NCL, we add the additional caveat that the household must previously have been a non-participant in order for an NCL to be classed as "new". With this approach, the unweighted sample indicates around 39 per cent of 2018 dated NCLs are categorised as "new".

[8] The 2020 HFCS indicates over 4 in 10 households had applied for credit within the past three years. However, the time period for this question overlaps with the last wave and the scope of the question covers applications for all types of credit, not just credit card debt. Therefore, a positive answer may not necessarily relate to credit cards.

[9] It should be noted that there are some instances where a simple subtraction is not possible. For example, where a balance from wave 3 is carried forward as "existing debt" in order to calculate revealed debt.

[10] Inaccuracies could arise firstly, because the characteristics required to calculate repayment according to an amortisation formula (current interest rate, maturity and outstanding balance) were self-reported in wave 3 and therefore may not be accurate. Second, a household may not have correctly self-reported the true composition of their debt in wave 3, implying there is a risk that a debt could be subjected to a different debt's amortisation characteristics. Third, we do not know exactly when a household completed the survey, therefore amortising would require making an assumption as to how many months of repayments have been made

4. **There are instances where "new" or "existing" debt may be over-stated.** For example, under our approach an NCL with an originating year of 2019 or 2020 is classed as new, but it might actually be a rolled-over existing loan. Likewise, if a household holds no new NCL debt but experienced an increase in balance between waves, our approach treats the excess above the wave 3 balance as revealed debt. However, doing this likely overstates the value of existing debt due to the approach implicitly assuming no deductions for repayment between waves.

5. **There are instances where "revealed" debt may be under-stated.** Our approach to identifying revealed debt often rests on assumptions around whether a household is a new participant or not, or how their balance has changed. This can lead to an underestimation of revealed debt. For example, if a household's NCL debt increases between waves and it is either not, or only partly, due to new borrowing, then the remaining increase is categorised as revealed debt. However, if the balance falls then revealed debt will not be identified. In general, because we have to account for debt repayment between waves, it is difficult for our approach to identify revealed debt if a balance falls; or put differently, identify where a household over-reported their debt initially.

6. **Credit card debt contains the most assumptions.** As a short-term debt vehicle, it has very different dynamics to personal and home loans. For example, a household may have a credit card but no outstanding balance. Some households will repay in full each month, while others may make minimum repayments and regularly carry balances forward. Therefore, the balance reported in the HFCS is dependent on many different factors and assumptions are required. The assumptions we apply are based on whether a household is a new card holder or not; whether they had recently applied for credit or not, and how their balance changed between waves.

3.3 Evaluating the improvement in coverage and quality

Once the debt has been carefully categorised, we can explore how the CCR has enhanced the accuracy of debt *coverage*. To do this, we first explore the debt composition of new participants in order to identify how much of their participation at the extensive margin (i.e. whether someone has any debt or not) is the result of holding truly "new" debt versus "revealed" debt. Next, we decompose the overall change in participation and change in outstanding balance between waves to understand the extent to which these changes are driven by the CCR revealing debt. This is followed by imagining what the results might be had the CCR not been incorporated (i.e. had the revealed debt remained unknown). We do this by simply removing the revealed debt and comparing the extent to which this would change the participation rates and outstanding balances reported in 2020.

between waves which may be too many or too few. Fourth, the HFCS was conducted during the COVID-19 pandemic and some households may have made use of forbearance measures which would not be accounted for by amortising using 2018 information.

Next, we consider how the CCR has improved the *quality* of debt information. This analysis consists of two parts. First, we focus on households with any revealed debt and quantify the impact of the CCR on the intensive margin (i.e. the number of loans a household has). Second, we focus on existing debt holders and identify if the household has any "improved" debt. For HMR mortgage debt, this is defined as having any loan for which the originating year, initial amount borrowed or initial loan length is recorded differently in 2020 than 2018 and the change is not the result of refinancing.[11] In the case of NCLs (where we do not have originating year information in 2018), the definition is restricted to the latter two characteristics only. For simplicity and to minimise the potential for compositional changes to confound the results, we consider only existing debt holders who experienced no increase in the number of loans between waves.[12]

4 Results

4.1 HMR mortgages

The HFCS panel indicates that 31.5 per cent of Irish households in 2020 had outstanding HMR mortgage debt. Amongst this group, the majority (close to eight in ten) hold some existing balance carried forward from 2018. A tenth hold new debt borrowed since the last wave. While around 15 per cent hold only revealed debt (Figure 2). However in total, over a quarter (27.3 per cent) of all households with HMR mortgage debt hold some form of revealed debt, whether an entirely revealed loan or a partly exposed balance.

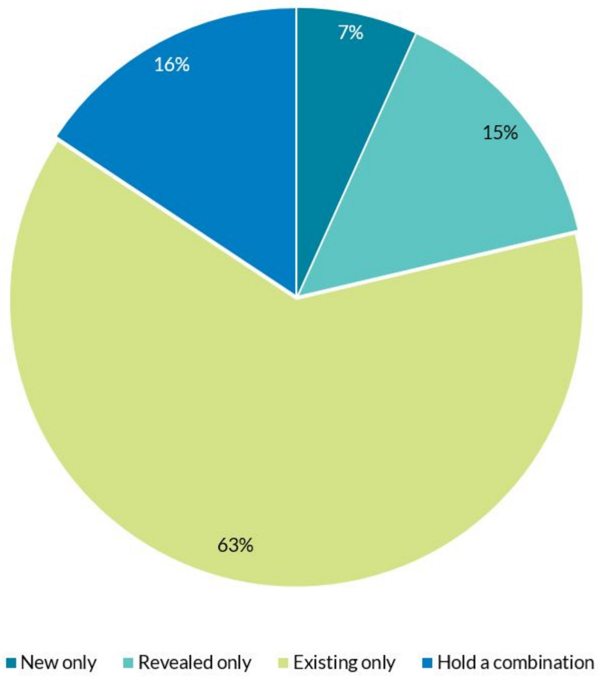
New participants (i.e. households who previously reported having no HMR mortgage debt in 2018) account for around a fifth of households with HMR mortgage debt outstanding in 2020. However, the majority of these households are not actually new borrowers, but rather households holding some pre-existing HMR mortgage debt which has been revealed by the CCR (Figure 3). This implies that new borrowers actually make up a minority of the households identified by the HFCS as being new HMR mortgage participants in 2020. Although the difference in value between new and revealed debt of new participants is smaller than the participation gap.

Comparing the 2018 and 2020 panel households, participation in HMR mortgage debt increased by 4.8pp (Table 4). Decomposing this change shows the contribution of revealed debt is more than twice that of new borrowing. The increase in participation for new borrowers is similar to the decrease associated with those who repaid their debt in full. As a result, if the revealed debt is removed, participation is largely unchanged at 26.9 per cent. This demonstrates how the CCR has greatly improved the coverage of debt and suggests a more subdued change between waves, which would better reflect the time it takes to become a new participant in this debt category.

[11] Current terms such as interest rate and maturity are not considered as a household may have changed the terms of their loan since the last wave. Without knowing which households renegotiated, it is difficult to determine the extent to which changes in current terms are driven by the CCR or deliberate negotiations. Further, in the case of NCLs, we do not consider improvements to originating year as this information is only available in HFCS 2020.

[12] We also repeat the analysis restricting on existing debt holders who experienced no change (increase or decrease) in the number of loans between waves and the results are very similar.

Figure 2: Share of HMR mortgage holders – by different debt types, 2020



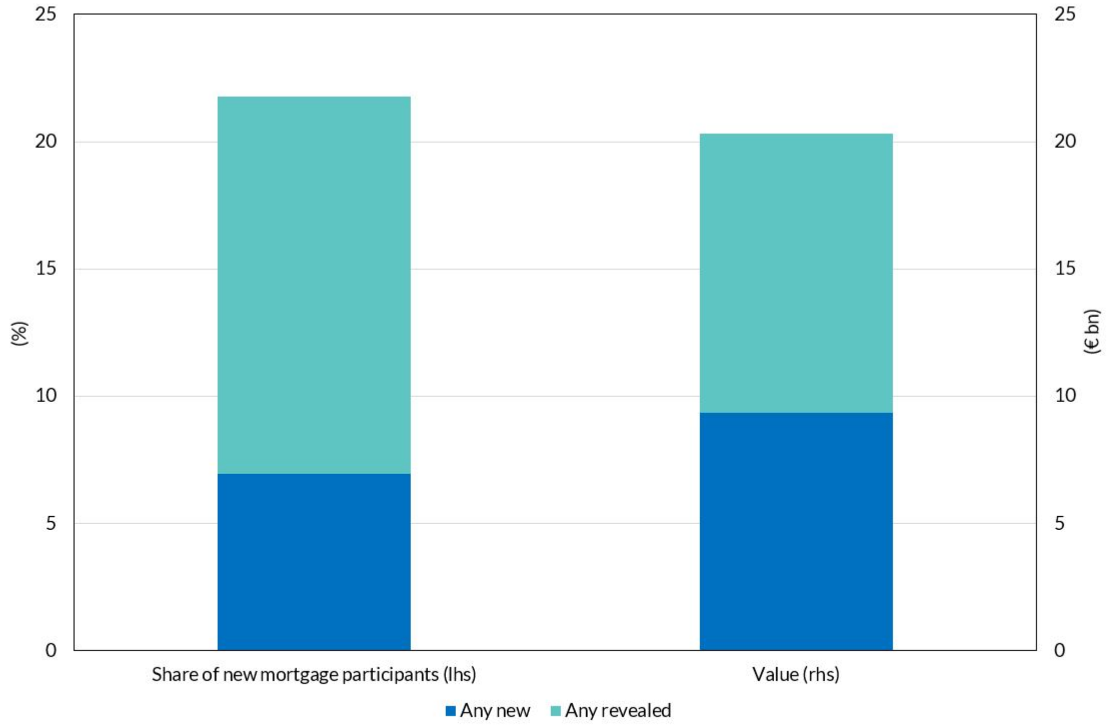
Source: HFCS panel (weighted to the 2018 population) and authors' own calculations.
Note: Some categories have been combined for statistical disclosure purposes.

In terms of the CCR's role in clarifying the value of debt, the panel shows that between 2018 and 2020, HMR mortgage debt rose by €15.1bn to €101.9bn (Table 5). This significant increase is driven by revealed debt which we estimate sums to €13.8bn. This is equivalent to 13.5 per cent of total HMR mortgage debt in 2020 and is greater than both the value of all new HMR mortgage borrowing (€12.3bn) and mortgage debt repaid since the last wave (€10.9bn).[13] As a result, excluding the revealed debt eliminates the large increase initially observed. Instead, the total value of HMR mortgage debt in 2020 would be €88.1bn, only slightly higher than 2018 levels reflecting a change more in line with the country's high home ownership rate.

An estimate of €13.8bn for the balance of revealed HMR mortgage debt might seem high. The scale might partly be explained by our weighting approach or the inherent characteristics of the panel, but it remains likely the CCR has helped to identify a substantial amount of debt, at least among panel households, which was previously under-reported in the HFCS.

[13] The value of new lending is derived from an estimated 48,000 new loans (equivalent to 7 per cent of total loans) and any balance increases that is likely the result of refinancing since 2018.

Figure 3: Participation and value of different debt types for new HMR mortgage participants, 2020



Source: HFCS panel (weighted to the 2018 population) and authors' own calculations.
Note: Some categories have been combined for statistical disclosure purposes.

Table 4. Participation of different HMR mortgage debt types

	Participation rate, (%)	**Net change in participation, 2018-2020 (pp)**
Any debt (2018, excl. CCR)	26.7	-
Any debt (2020, incl. CCR)	31.5	4.8
Net change consists of:		
Any new		2.2
Any revealed		4.7
Repaid debt in full		-2.0
Any debt (2020, excl. revealed)	26.9	0.2

Source: HFCS panel (weighted to the 2018 population) and authors' own calculations.
Note: Some debt categories grouped for statistical disclosure purposes. Any discrepancies due to rounding and grouping of categories.

Table 5 also shows that removing the revealed debt reduces the median HMR mortgage debt. This is interesting as the median balance for holders of revealed debt only (€93,513) is lower than that of only new debt (€208,842). Given the number of households holding some revealed debt is more than 2.7 times the number holding some new debt, we might have expected the removal of revealed debt to increase the median. The reduction potentially points to the large values of some revealed debts.

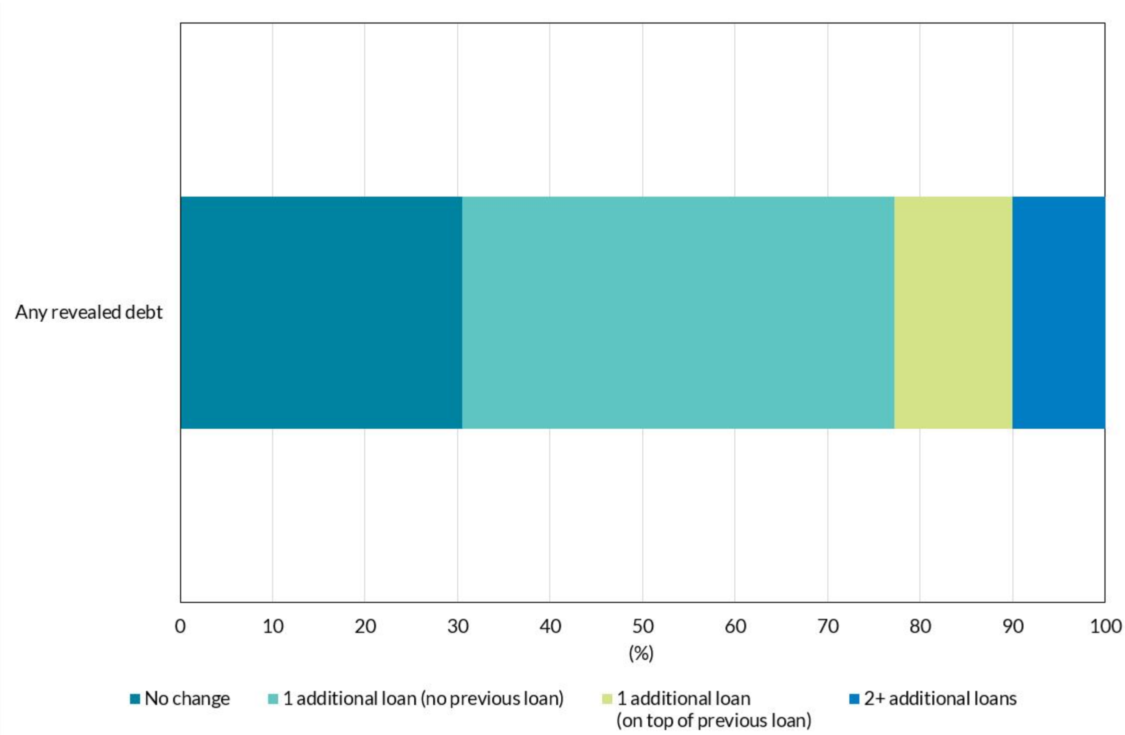
Table 5. Total and median outstanding balance of HMR mortgage debt types

	Total outstanding balance (€bn)	Net change in balance, 2018-2020 (€)	Median outstanding balance (€)
Any debt (2018, excl. CCR)	86.7	-	128,000
Any debt (2020, incl. CCR)	101.9	15.1	128,081
Net change consists of:			
New debt only		9.0	208,842
Revealed debt only		10.7	93,513
Existing debt only		-8.8	121,669
Holds a combination		6.3	130,916
Repaid debt in full		-2.1	25,000
Any debt (2020, excl. revealed)	88.1	1.3	123,349

Source: HFCS panel (weighted to the 2018 population) and authors' own calculations.
Note: 2018 data excludes the CCR and is based on self-reported values from HFCS respondents. Any discrepancies due to rounding.

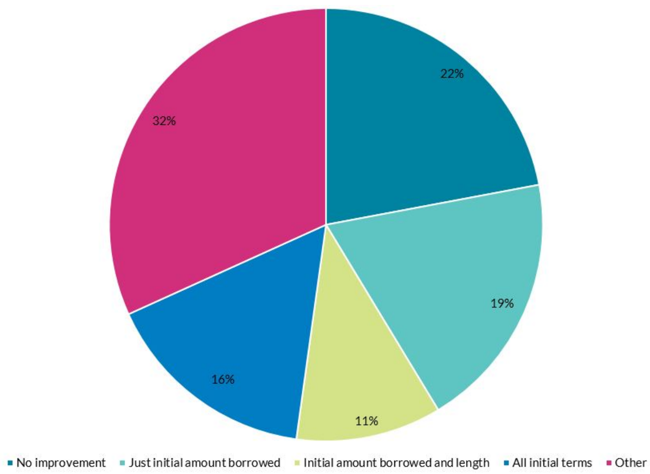
Turning now to how the CCR has improved the quality of debt information captured by the HFCS. Almost 7 in 10 households with revealed mortgage debt experienced a change in the composition of their debt (Figure 4). Specifically, 46.7 per cent went from having no HMR mortgage loans in 2018 to one in 2020. For 12.7 per cent, the inclusion of the CCR added at least one additional loan on top of previous holdings. While, a tenth now have 2 or more additional loans. However, it is important to note that a change in composition does not necessarily mean a change in balance. For example, some households in the last wave may have reported the right balance but the wrong composition because they elected to combine their loans for easier or quicker reporting.

Figure 4: Share of households holding any revealed HMR debt – by change in no. of loans, 2020



Source: HFCS panel (weighted to the 2018 population) and authors' own calculations.
Note: Some categories have been combined for statistical disclosure purposes.

Figure 5: Share of households holding existing HMR debt that experienced improvements in characteristics - by type of improvement, 2020



Source: HFCS panel (weighted to the 2018 population) and authors' own calculations.
Note: Some categories have been combined for statistical disclosure purposes.

Such corrections are not limited to revealed debt holders. Households carrying forward existing debt also benefit from the CCR more precisely capturing their loan information. Conditional on only holding existing HMR mortgage debt and not experiencing an increase in number of loans between waves, the panel indicates that 45 per cent of households experienced an improvement in how the initial terms of their loans were documented; highlighting how self-reported debts can be susceptible to misreporting. Similar conclusions are reached by McCarthy and McQuinn (2016) who find households have considerable difficulty recalling how much they paid for their home. Biancotti et al. (2008) also finds basic socio-demographic information can be misreported and that the measurement of debts in the Italian Survey of Household Income and Wealth can be unreliable.

In the case of the Irish HFCS, the initial amount borrowed was the characteristic most likely to experience a correction (Table 6). However, 16 per cent of the sub-sample considered had all three initial terms updated following the inclusion of the CCR (Figure 5). Further analysis indicates that corrections were more likely to be for initial under-reporting. However, considering whether a correction is large or not (defined as correcting for a gap of more than 2 years for origin date and initial length of loan, and more or less than 10 per cent of initial amount borrowed), the scale of the change is relatively minimal for origin date and initial length. In contrast, it was large for over 40 per cent of those whose initial amount borrowed was corrected.

This suggests that households self-report information about years or dates that is relatively close to actual values, but find it more challenging to recall exact monetary amounts borrowed. While all three characteristics considered apply from the same point in time in the past, the results suggest that they do not constitute the same memory problem for households. Alternatively, it could be that the household respondent did not lead on contracting the mortgage and therefore lacks knowledge in this specific respect.

Table 6. Share of households experiencing different types of improvement to HMR mortgage characteristics, 2020 (conditional on experiencing an improvement)

	Origin date	**Initial amount borrowed**	**Initial length of loan**
Experienced an improvement	39.8	57.1	44.1
Conditional on experiencing an improvement			
Any initial under-reporting	43.1	53.0	60.7
Any initial over-reporting	35.5	47.9	39.1

Source: HFCS panel (weighted to the 2018 population) and authors' own calculations.
Note: Results based on 2020 wave of panel households who hold existing HMR mortgage debt and did not experience any increase in number of loans held since last wave. Figures do not sum to 100 as it is possible for borrowers to misreport in more than one category.

Given the time that may have passed between origination of HMR mortgage debt and present day, it is perhaps unsurprising that households struggle to recall this information. Had current terms been assessed instead, it is possible households would have performed better. For example, using the US Survey of Consumer Finances, Bucks and Pence (2008) find that most borrowers seem to know basic mortgage terms, such as type of mortgage, amortisation period and annual mortgage payment. However, there is less consistency between borrower-reported and lender-reported data on terms such as year of origination. They also find that borrowers with adjustable-rate mortgages regularly underestimate their interest rate or are not aware of how much it could change.

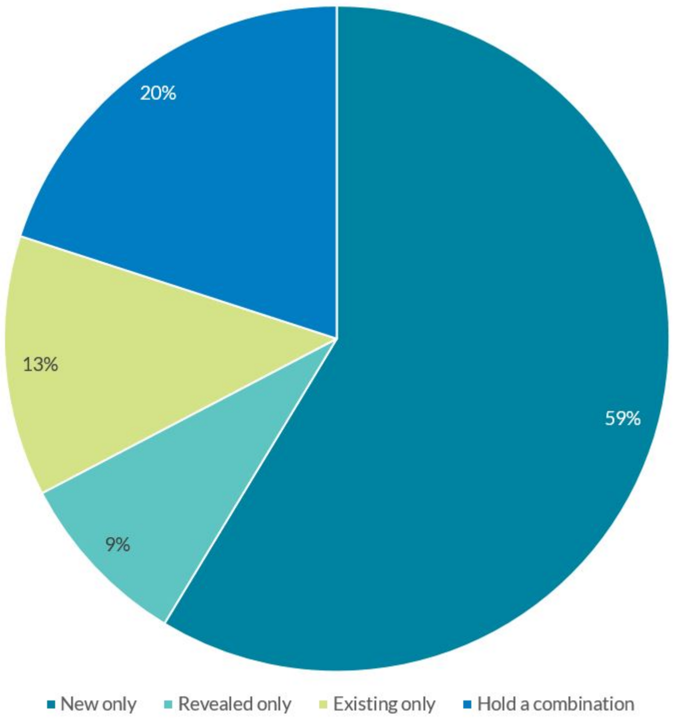
4.2 Non-collateralised loans

HFCS panel data shows over 4 in 10 Irish households (42.8 per cent) hold an outstanding NCL in 2020. Of these, the majority (73 per cent) hold some new debt borrowed since the last wave. Around three in ten hold an existing balance carried forward from 2018 (Figure 6). While, close to a fifth hold revealed debt. This is a slightly smaller proportion to that observed for HMR mortgage debt.

Among the households with outstanding NCL debt in 2020, around half are new participants (i.e. previously reported no NCL debt in 2018) and, unlike HMR mortgage debt, our approach finds the majority of these new participant households are in fact new NCL borrowers (Figure 7). Nevertheless, around 18 per cent of new participants are identified only due to revealed debt; and while the share of new participants identified as new only borrowers is around 4 times the size of the share for only revealed debt, the value of revealed NCL debt is 1.3 times that of new NCL borrowing.

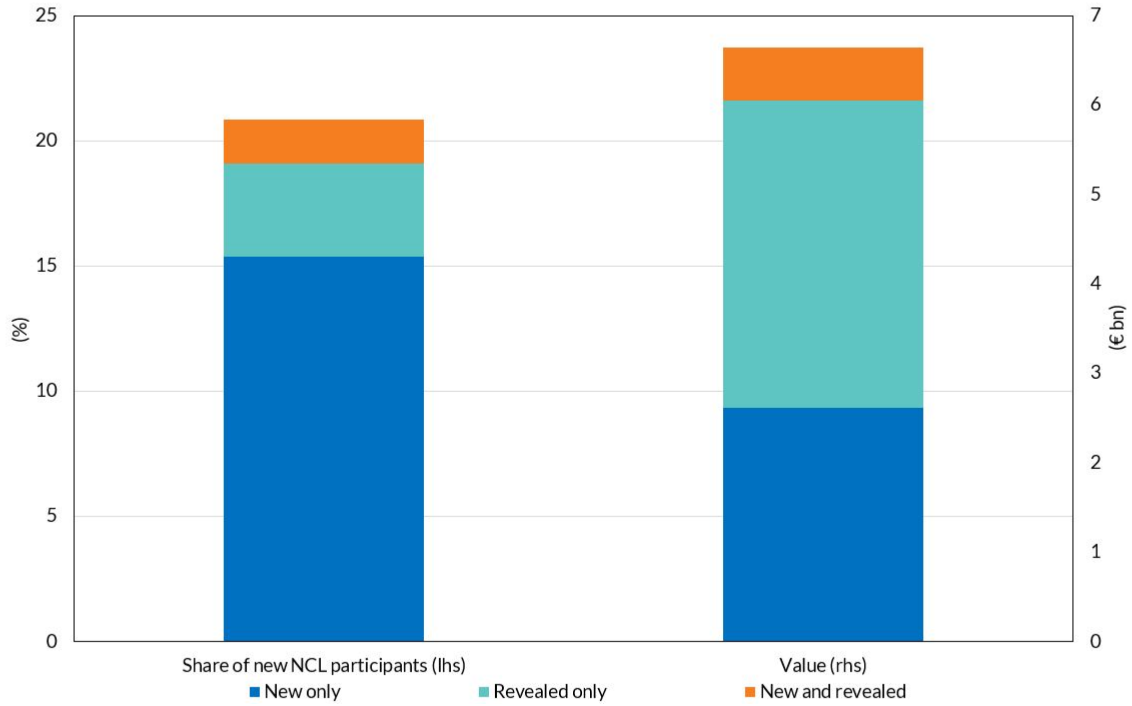
Comparing the 2018 and 2020 panel households, participation in NCL debt increased by 14.2pp (Table 7). Decomposing this change shows that new borrowers contributed most to the increase with the contribution of revealed debt comparatively small. As a result, excluding the revealed debt does not significantly lower the NCL participation rate. It would still remain 10.5pp higher than 2018 levels, at 39.1 per cent.

Figure 6: Share of NCL holders – by different debt types, 2020



Source: HFCS panel (weighted to the 2018 population) and authors' own calculations.
Note: Some data has been suppressed or combined for statistical disclosure purposes.

Figure 7: Participation and value of different debt types for new NCL participants, 2020



Source: HFCS panel (weighted to the 2018 population) and authors' own calculations.

Table 7. Participation of different NCL debt types

	Participation rate, (%)	**Net change in participation, 2018-2020 (pp)**
Any debt (2018, excl. CCR)	28.6	-
Any debt (2020, incl. CCR)	42.8	14.2
Net change consists of:		
New debt only		15.4
Revealed debt only		3.7
Existing debt only		-
Holds a combination		1.8
Repaid debt in full		-6.7
Any debt (2020, excl. revealed)	39.1	10.5

Source: HFCS panel (weighted to the 2018 population) and authors' own calculations.
Note: Some debt categories grouped for statistical disclosure purposes. Any discrepancies due to rounding and grouping of categories.

In terms of the CCR's role in clarifying the value of NCL debt, the outstanding balance of all revealed debt is estimated to be €4.3bn (Table 8). Unlike HMR mortgage borrowing, the balance of new debt is largest at €5.6bn. This figure, while consistent with approximately six in 10 NCLs having origination dates of 2019 and 2020, is higher than aggregate new lending data might indicate.[14] One explanation for the large value of new debt is that this reflects the panel households being more likely to hold this debt compared to the full sample.

Table 8. Total and median outstanding balance of NCL debt types

	Total outstanding balance (€bn)	**Net change in balance, 2018-2020 (€)**	**Median outstanding balance (€)**
Any debt (2018, excl. CCR)	10.9	-	6,700
Any debt (2020, incl. CCR)	11.3	0.4	7,027
Net change consists of:			
New debt only		2.5	5,748
Revealed debt only		3.4	5,829
Existing debt only		-0.9	4,814
Holds a combination		1.2	12,824
Repaid debt in full		-5.9	6,000
Any debt (2020, excl. revealed)	7.0	-3.9	6,364

Source: HFCS panel (weighted to the 2018 population) and authors' own calculations.
Note: 2018 data excludes the CCR and is based on self-reported values from HFCS respondents. Any discrepancies due to rounding.

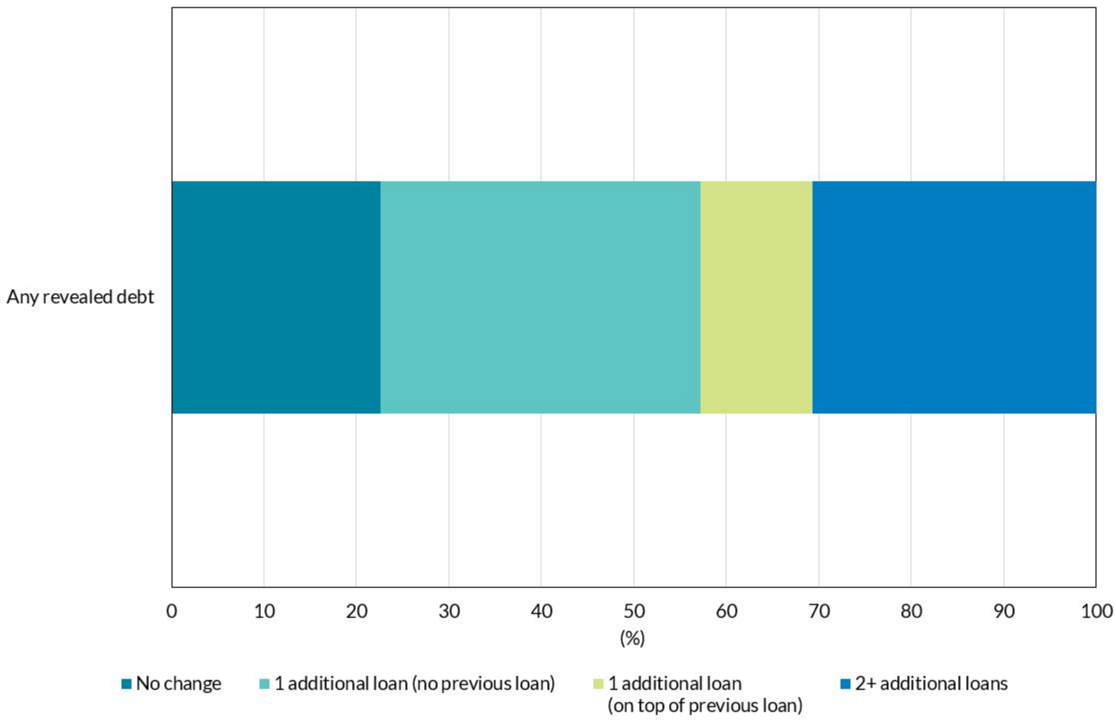
However, it could also reflect limitations in the methodology which is leading to new debt being over-identified at the expense of other categories. For example, some of this new debt may reflect roll-over loans which are better classified as "existing". This is supported by the large value of debt repaid (€-9.5bn) and explains why the net change in balance for holders of new only debt (€2.5bn) is lower than the value of total new debt (€5.6bn). Either households rolled over smaller balances or they repaid their larger 2018 balances before taking out smaller new loans. Our methodology treats both scenarios the same, which is why the value of repaid debt acts as an appropriate counter-balance

[14]BPFI data for personal loan drawdowns is only available from the start of 2020. However, looking at the quarters covered by the HFCS field work period, the 2020 drawdown figures suggest a total figure of €2.4bn.

to the value of new debt.

As a result, despite the large increase in supposedly new NCL lending, Table 8 shows that, in the absence of the CCR, the outstanding balance of NCL debt would have decreased (-€3.9bn), suggesting that households did in fact repay a large amount of debt between waves. This result is consistent with the ongoing trend of Irish households deleveraging.

Figure 8: Share of households holding any revealed NCL debt – by change in no. of loans, 2020



Source: HFCS panel (weighted to the 2018 population) and authors' own calculations.

Finally, we also observe that the CCR has improved the quality of NCL information captured by the HFCS. (Figure 8) Specifically, of those households with any revealed debt, 34.6 per cent went from having no NCLs in 2018 to one in 2020. For 12.1 per cent, the inclusion of the CCR added at least one additional loan on top of previous holdings. While 30.7 per cent now have two or more NCLs in 2020 than they did in 2018. The remaining households with any revealed debt (22.6 per cent) self-reported the correct number of loans in the last wave but under-reported the outstanding balance.

In terms of how the CCR has helped to more precisely capture loan information, the panel shows that, after conditioning on only households holding existing NCL debt and having the same number of loans as last wave, 85.1 per cent of households experienced an improvement in how the initial terms of their loans were documented. The most common improvement was updates to just the initial amount borrowed, followed by both amount borrowed and length.

Further analysis indicates that the updates to initial amount borrowed were more likely to be correcting for initial under-reporting. Whereas for the length of loans, it was more likely to be for over-reporting (Table 9). However, considering whether a correction is large or not (defined as correcting for a gap of more than 2 years for initial length of loan, and more or less than 10 per cent of initial amount borrowed), the scale of the change is relatively minimal for initial length. In contrast, the correction was large for around 80 per cent of those experiencing an improvement to initial amount borrowed. This matches the findings for HMR mortgage debt.

Table 9. Share of households experiencing different types of improvement to NCL characteristics, 2020 (conditional on experiencing an improvement)

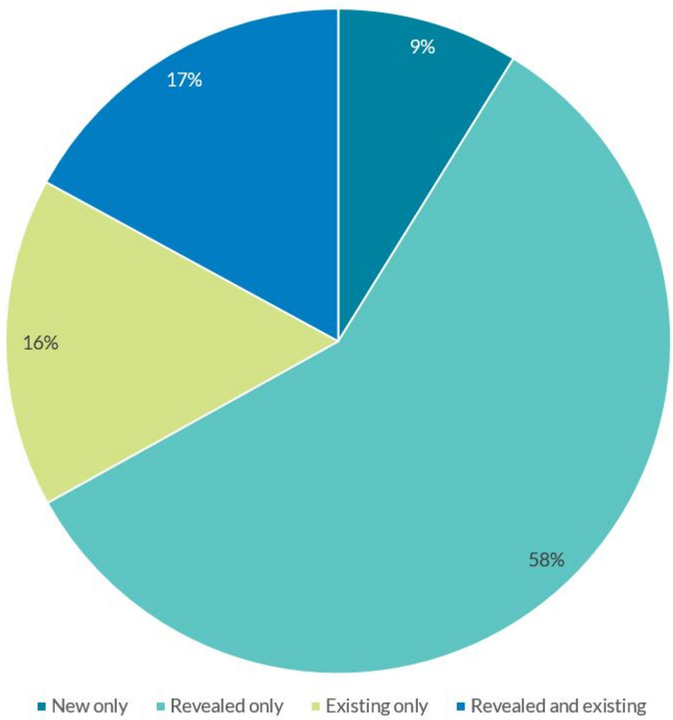
	Initial amount borrowed	**Initial length of loan**
Experienced an improvement	77.7	41.1
Conditional on experiencing an improvement		
Any initial under-reporting	59.4	36.7
Any initial over-reporting	46.5	41.6

Source: HFCS panel (weighted to the 2018 population) and authors' own calculations.
Note: Results based on wave 4 sample of panel households who hold existing NCL debt and did not experience any increase in number of loans held since last wave. Figures do not sum to 100 as it is possible for borrowers to misreport in more than one category.

4.3 Credit cards

HFCS panel data shows that six in ten Irish households had a credit card in 2020, with a smaller proportion (27.2 per cent) carrying an outstanding balance on their card. This represents a 13.2pp increase on 2018. Among these households, a large share (around three quarters) hold some revealed debt (Figure 9).

Figure 9: Share of households with a credit card balance – by different debt types, 2020

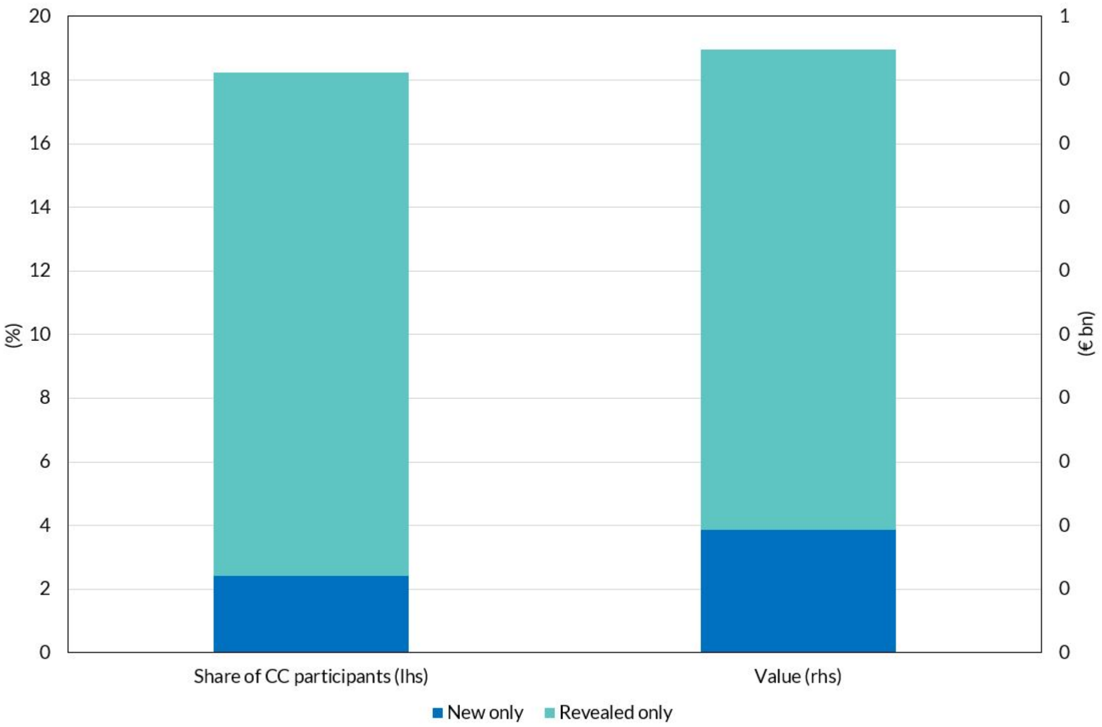


Source: HFCS panel (weighted to the 2018 population) and authors' own calculations.
Note: Results based on 2,808 observations in both wave 3 (2018) and wave 4 (2020).

That is, a large share experienced an increase in credit card balance between waves which is not the result of being a new card holder or recently applying for credit. Less than a tenth hold debt which is likely to reflect new borrowing. While, a third hold an existing balance which is either less than or equal to that held in 2018.

New participants (i.e. those with an outstanding balance in 2020 when previously they had none in 2018) account for two-thirds of households with an outstanding balance. For new credit card participants, the majority of debt is revealed, with the value of this debt also exceeding the value of new credit card debt (Figure 10).

Figure 10: Participation and value of different debt types for new credit card holders, 2020



Source: HFCS panel (weighted to the 2018 population) and authors' own calculations.
Note: Results based on 2,808 observations in both wave 3 (2018) and wave 4 (2020).

Decomposing the change in participation between waves shows that new borrowers account for just 2.4pp of the net change in participation (Table 10). This is less than the decrease associated with those who repaid their debt in full. Instead, the large increase in participation between waves is driven by households with revealed debt.

Excluding this revealed debt, the participation rate for credit card debt in 2020 would have been 11.4 per cent. This represents a decline of 2.6pp, as opposed to the original double digit increase if comparing the HFCS results at face-value. Similar to the NCL findings, this implies that the CCR has greatly improved the coverage of debt.

Table 10. Participation of different credit card debt types

	Participation rate, (%)	Net change in participation, 2018-2020 (pp)
Any debt (2018, excl. CCR)	14.0	-
Any debt (2020, incl. CCR)	27.2	13.2
Net change consists of:		
New debt only		2.4
Revealed debt only		15.8
Existing debt only		-
Existing and revealed		-
Repaid debt in full		-5.0

Source: HFCS panel (weighted to the 2018 population) and authors' own calculations.
Note: 2018 data currently excludes CCR and is based on self-reported values from HFCS respondents. Any discrepancies due to rounding.

A trend reversal is also observed for outstanding balance. Table 11 shows that the outstanding balance of all revealed debt is around €0.7bn; equating to 64 per cent of the total credit card debt in 2020 and roughly €0.3bn greater than the combined value of new borrowing and credit card debt repaid since the last wave. Excluding the revealed debt, the total value of credit card debt in 2020 would be approximately €0.4bn, which would actually represent a 30 per cent reduction on 2018 levels.

Table 11. Total and median outstanding balance of credit card debt types

	Total outstanding balance (€bn)	Net change in balance, 2018-2020 (€)	Median outstanding balance (€)
Any debt (2018, excl. CCR)	0.5	-	1,200
Any debt (2020, incl. CCR)	1.0	0.5	800
Net change consists of:			
New debt only		0.1	1,094
Revealed debt only		0.4	480
Existing debt only		-0.1	686
Holds a combination		0.3	3,232
Repaid debt in full		-0.1	900
Any debt (2020, excl. revealed)	0.4	-0.2	1,000

Source: HFCS panel (weighted to the 2018 population) and authors' own calculations.
Note: 2018 data currently excludes CCR and is based on self-reported values from HFCS respondents. Any discrepancies due to rounding.

It is worth noting that due to the assumptions we make to apply our identification approach to credit cards, the value of existing debt may be understated.[15] In addition, there are some imperfections with how we distinguish between "new" and "revealed" credit card debt. Namely, under our approach, all existing card holders who experienced an increase in balance are categorised as holding revealed debt. Yet it is likely that some of these households are in reality, better classed as new borrowers.

However, confidence is gained by considering the external context. HFCS data was collected between July 2020 and January 2021, encompassing a time when pandemic restrictions were tightened from October 2020 onwards. This would have reduced the

[15]The definitions presented in Table 3 imply that it is not possible to hold both "new" and "existing" credit card debt, or "new" and "revealed". In addition, "existing" debt only reflects balances which are less than or the same as the last wave but this could just reflect a lower than normal balance at the particular time of survey completion.

opportunities to spend (Byrne et al. 2020). Under such unique circumstances, it is not unreasonable to assume that increases in balance are more likely to reflect revealed as opposed to new debt, particularly in the absence of information to confirm otherwise. This assumption is also supported by daily card payments data indicating that between HFCS waves, there were fewer active credit cards in issue and lower levels of new spending.

4.4 Summary

In total, 32.2 per cent of households are identified as holding some revealed debt according to the panel analysis. Conditional on being a debt participant, the ownership rate rises to 47.6 per cent. The average (median) household holds €35,078 (€3,818) worth of revealed debt, with the largest holdings reaching €707,602.

Across all households, the value of revealed debt is estimated to sum to at least €18.8bn, equivalent to around an eighth of the total debt held by households in 2020. Table 12 summarises the findings across the three debt types.

Table 12. Revealed debt – participation and outstanding balance, overall and across debt types, 2020

	Participation			**Value**	
	Share of HHs with revealed debt (%)				
	All households	*Conditional on holding debt*	*Estimated initial measurement error (%)*	*Outstanding balance (€bn)*	*Estimated initial measurement error (%)*
HMR	8.6	27.3	-15.0	13.8	-14.0
NCL	9.6	22.4	-9.0	4.3	-38.0
Credit Card	20.5	75.2	-58.0	0.7	-64.0
Total	32.2	47.6		18.8	

Source: HFCS panel (weighted to the 2018 population) and authors' own calculations.

For HMR mortgage debt, revealed debt holders constitute 27.3 per cent of all borrowers but make up the vast majority of the total value of revealed debt. Comparing the total outstanding balance of HMR mortgage debt in 2020 with and without the revealed debt suggests that the CCR has helped to correct an initial measurement error of -15 per cent for participation and -14 per cent for outstanding balance.

In regards to NCL debt, 22.4 per cent of borrowers hold some revealed debt. Excluding this debt from the 2020 results shows that participation would have been 9 per cent lower and outstanding balance 38 per cent lower.

Finally, credit card debt shows the largest share of revealed debt holders. The implied initial measurement error that the CCR has corrected for in this type of debt is -58 per cent in the case of participation and -64 per cent for outstanding balance. These results echo earlier studies that also found unsecured debts to have lower correspondence than mortgages and secured loans. The scale of under-reporting we find is also consistent. For example, Brown et al., (2015) find that aggregate credit card debt implied by borrower data is up to 40 percent lower than that implied by register data, while Zinman (2009) found the aggregate credit card debt levels implied from the SCF to be only half that of lender-reported levels.

The prevalence of revealed credit card debt compared to the other debt types suggests that smaller balances are more susceptible to misreporting. One explanation for this could be that households do not consider small credit card balances to warrant reporting. Zinman (2009) also identified the risk of unintentional under-reporting in credit card debt, conjecturing that this may be due to the complexity of credit card borrowing (multiple cards across multiple household members) or that the act of purchasing with a credit card is less salient.

5 Who holds revealed debt?

Given a large share of households hold revealed debt, it is worth exploring the attributes of these households to understand if they differ from the wider population. Table 13 shows the household characteristics of those holding any revealed debt alongside specifically revealed HMR, NCL or credit card debt.

Table 13. Characteristics of households holding any revealed debt, by debt type, 2020 (%), average (unless otherwise stated)

	HMR	NCL	Credit Card	Any revealed
Age (years)	48.5	50.6	54.6	52.3
Female (%)	58.3	53.4	55.2	56.8
Own their home (%)	100.0	75.2	89.8	86.9
Principle Economic Status (%)				
Employed	66.4	48.9	55.0	55.5
Self-employed	13.6	6.5	7.0	8.1
Unemployed	1.7	5.9	3.1	4.0
Retired	4.9	19.8	25.5	19.8
Other inactive	13.4	18.9	9.4	12.6
Gross income				
1st quintile	10.9	13.8	7.0	10.1
2nd quintile	7.6	12.6	11.5	12.1
3rd quintile	18.4	24.0	21.8	22.6
4th quintile	26.8	30.4	26.8	25.8
5th quintile	36.3	19.2	32.9	29.5
Median (€)	82,160	66,200	79,310	74,700
Education				
Primary	3.5	8.3	3.9	4.8
Secondary	40.5	44.0	30.7	36.6
Post-secondary	56.1	47.7	65.4	58.6
No. of incomes per adult in HH	0.85	0.90	0.94	0.89
Net wealth (€ median)	242,793	173,683	371,737	269,941
Debt service to income > 30% (%)	16.7	13.3	6.1	9.2
Number of debts	3.16	3.16	2.72	2.68
Balance sheet complexity*				
Low	1.7	11.4	3.9	6.3
Moderate	23.8	29.6	22.4	26.1
High	74.5	59.0	73.7	67.6

Source: HFCS panel (weighted to the 2018 population) and authors' own calculations.
Note: Principle economic status achieved by household reference person.
* Balance sheet complexity: "Low" = 4 or less types of balance sheet items; "Moderate" = 5 or 6 different types of balance sheet items; "High" = 7 or more types of balance sheet items.

For all three individual debt types, the share of households holding revealed debt increases with education. A similar pattern is observed with income, although this is less true for NCLs where the first quintile has a higher prevalence than the second and the share peaks in the fourth rather than fifth quintile. Workers make up the largest share of revealed debt holders, particularly for HMR debt; consistent with this being an important determinant of home ownership. Revealed debt holders have higher median gross household income than the wider population. The median household with revealed debt also has higher net wealth, with this true for all the individual debt types except NCL debt, where median net wealth is lower.

Across the debt types, households with any revealed HMR mortgage and NCL debt have, on average, a greater number of debts and higher debt service to income ratios. Revealed credit card debt holders are on average older and wealthier than the other debt types. They also have the highest share of retirees suggesting that small card balances may be the only debt for many of these households.

Interestingly, there is a positive association with balance sheet complexity. Households with highly complex balance sheets (defined as having 7 or more different types of assets or liabilities) make up over 67.6 per cent of any revealed debt holders. However, this result is sensitive to how complexity is defined. Under our definition, the share of all panel households in each category of balance sheet complexity are similar, although highly complex is still the most common category and households in the high category are more likely to hold debt.[16] Selecting a different threshold may therefore produce different results. Nevertheless, it is intuitive to think that households who have to recall and self-report a broader range of items are more likely to benefit from the inclusion of the CCR.

To examine the results more formally, we estimate a logit regression model that predicts the probability that a household has any revealed debt, be that HMR mortgage, NCL or credit card.[17] The marginal effects of the model are presented in Table 14, with controls added incrementally up to the full model shown in Column 5. The results are aligned with the previous descriptives. Having a moderately complex balance sheet, defined as having 5 or 6 different types of balance sheet items, is associated with increasing the likelihood of holding revealed debt by 15.9pp compared to having a balance sheet of low complexity. The marginal effect is even greater (39.7pp) if a household has a highly complex balance sheet.

Compared to being employed, none of the alternative work statuses appear to increase the likelihood of holding revealed debt. Similarly, there is a lack of significance for gender and wealth. The statistical significance of education diminishes as more controls are added. Likewise, the statistical significance of the positive association between higher income and the likelihood of holding revealed debt is eliminated once balance sheet complexity is included. Similar occurs to the home-ownership variable, suggesting that in the absence of balance sheet complexity, income and home-ownership are acting as proxies for the extent to which a household is indebted. Age appears to increase

[16] 24.8 per cent of all panel households are in the "low" category, 33.8 per cent "moderate" and 41.8 per cent "high".

[17] A logit model allows the estimated effects of explanatory variables on a binary outcome (holding revealed debt or not) to be bounded between 0 and 1. Positive (negative) coefficients indicate that a variable is associated with increasing (decreasing) likelihood. The marginal effects reported in this paper describe the change in the probability of holding revealed debt, given a one unit change in each explanatory variable, holding all the other explanatory variables at their sample mean. Note, we used all five implicates of the HFCS data in our regressions but we also re-performed the regressions using each of the five individual implicates in turn and found little difference in the results.

likelihood and enters non-linearly, but its statistical significance also reduces somewhat once balance sheet complexity is added.

Table 14. Logit estimation of likelihood of holding any revealed debt

	1	2	3	4	5
Female	-0.0219	-0.0286	-0.021	-0.0248	-0.0311
	(-0.83)	(-1.06)	(-0.81)	(-0.95)	(-1.20)
Age	0.0394***	0.0306***	0.0284***	0.0238***	0.0202**
	(5.89)	(4.23)	(4.03)	(3.40)	(2.88)
Age squared	-0.000368***	-0.000317***	-0.000284***	-0.000233***	-0.000191**
	(-6.29)	(-4.82)	(-4.49)	(-3.76)	(-3.06)
Highest Education Level: Secondary	0.120***	0.104***	0.0823*	0.0800*	0.065
	(4.14)	(3.40)	(2.43)	(2.33)	(1.80)
Highest Education Level: Tertiary	0.230***	0.182***	0.133***	0.130**	0.0933*
	(6.66)	(4.99)	(3.42)	(3.28)	(2.32)
Own home		0.205***	0.206***	0.147***	0.0331
		(8.47)	(5.45)	(3.36)	(0.64)
Work Status – Self-employed		-0.042	-0.0294	-0.0198	-0.0614
		(-1.09)	(-0.73)	(-0.48)	(-1.72)
Work Status – Unemployed		-0.032	0.012	0.0247	0.0272
		(-0.60)	(0.21)	(0.43)	(0.47)
Work Status – Retired		0.029	0.0542	0.0731	0.0926
		(0.51)	(0.97)	(1.30)	(1.65)
Work Status – Other inactive		0.0196	0.0454	0.0509	0.0714
		(0.50)	(1.12)	(1.23)	(1.72)
Income – 2nd Quintile			0.0131	0.0103	-0.0271
			(0.40)	(0.31)	(-0.73)
Income – 3rd Quintile			0.152***	0.149***	0.079
			(4.00)	(3.74)	(1.92)
Income – 4th Quintile			0.152***	0.117**	0.0423
			(3.29)	(2.60)	(0.90)
Income –5th Quintile			0.173***	0.134**	0.0708
			(3.71)	(2.77)	(1.43)
Holds any new debt				0.0226	-0.04
				(0.86)	(-1.54)
Holds any existing debt				0.151***	0.0728*
				(4.55)	(2.23)
Balance sheet complexity – Moderate					0.159***
					(6.70)
Balance sheet complexity – High					0.397***
					(10.83)
Observations	14,040	14,040	14,040	14,040	14,040
Additional controls included *			Y	Y	Y

Source: HFCS panel (weighted to the 2018 population) and authors' own calculations.
Note: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1
Results based on a logit estimation for likelihood of holding any revealed debt in 2020. Panel weights applied and all five implicates used, with standard errors clustered at the household level.
* Additional controls include wealth categories which were not significant.
Balance sheet complexity defined as number of different types of balance sheet items. Low = 4 or fewer; Moderate = either 5 or 6 and High = 7 or more. Reference category for education level= primary; for work status = employed; for income and wealth = 1st quintile and for balance sheet complexity = low.

For robustness, we also considered alternative measures of balance sheet complexity. These included: the number of loans held (covering HMR mortgage, other property and NCLs); the number of debts held (which also captures private loans, overdrafts and credit cards); number of types of debt, number of balance sheet items, and number of types of balance sheet items as a numeric as opposed to categorical variable. The results are presented in Table A.3 of the Appendix. Under all five definitions, balance sheet complexity is statistically significant. The largest marginal effect is observed under number of types of debt, where an additional type is associated with a 45.7pp increase in the probability that a household holds revealed debt. The size of this effect is 1.7 times larger than that of an increase in number of debts (26.8pp), suggesting it is not just quantity that is important but also diversity. Separate regressions were also run for each of the three debt types with a similar association found between balance sheet complexity and likelihood of holding revealed debt (Table A.4 of the Appendix). The coefficients are largest for credit card debt.

As mentioned, it is possible that our results are sensitive to the thresholds used to create our categorical variable for balance sheet complexity. Therefore, we also re-perform the regression under two different definitions which alter the thresholds for low, moderate and high complexity. The results in Table A.5 of the Appendix show the same association, consistent with our original model. Under both sets of alternative thresholds, the marginal effect of having a moderately complex balance sheet is higher than our baseline results, but having a highly complex balance sheet still has the greatest marginal effect.

Like Bucks and Pence (2008), our results potentially add weight to the hypothesis that misreporting errors may occur because it is costly to acquire accurate information on household debts. For the previous authors, the evidence rested on finding older, lower-income, and minority borrowers (i.e. groups with potentially fewer resources and lower financial literacy levels) were more likely to report they "don't know" their mortgage terms.[18] In our case, evidence is provided by the intuition behind the balance sheet complexity result. More debts (and other instruments) to report implies greater time and effort by the household correspondent to source, compile and report this information. Households may perceive the costs of this activity to exceed the benefits.

The result also likely relates to household size. Households with highly complex balance sheets have an average of 3.35 household members aged 16 or older compared to 2.71 for households with low complexity balance sheets, and the share of single adult households with revealed debt is around half that of households with 2 or more adults. Brown et al., (2015) also found a closer match for households with one adult than for households with 2 or more adults and notes this may shed some interesting light about how household members interact about financial matters.

6 Implications

6.1 Macroeconomic trends

The identification of a large amount of revealed debt has implications for our understanding of the household sector's overall indebtedness. Excluding it, the panel shows that the debt participation rate in 2020 would be 13.4 per cent lower and total outstanding balance 13.1 per cent smaller (Table 15).

[18]The HFCS does provide information on financial literacy but there are comparability issues. In 2018, three questions were asked but with a low response rate. While in 2020, only one was asked (on inflation) though it had a significantly higher response rate. Notwithstanding, tentative analysis of the responses to the 2018 questions suggest that financial literacy levels between households with and without revealed debt are similar. The role of financial literacy remains an area for future research.

Table 15. Overall debt participation and outstanding balance, with 2018-2020 changes

	Participation (%)	Outstanding balance (€bn)
2018	52.5	120.8
2020 (incl. CCR)	67.7	142.7
2020 (excl. revealed)	58.6	124.0
Changes		
2018 – 2020 (incl. CCR)	+15.1pp	+22.0bn
2018 – 2020 (excl. revealed)	+6.0pp	+3.2bn

Source: HFCS panel (weighted to the 2018 population) and authors' own calculations.

For the latter, it is clear that revealed HMR debt has been key to correcting the initial error. This is expected given the larger balances associated with this type of debt. It is less clear what is driving the participation bias. On face value, the panel shows that debt participation increased 15.1 percentage points from 52.5 per cent in 2018 to 67.7 per cent in 2020. Having carefully identified the composition of debt held at the household level, we can identify what debt type is driving the aggregate participation increase. Recall that in order to become a new participant a household must have had no debt in 2018 but some in 2020. For this to occur, the household must either have become a new borrower since the last wave or had its debt revealed.

Decomposing the 15.1pp change into the different types of debt a household can hold and the extent to which that debt is "new", "revealed" or "unclassified" (defined as out of the scope of our methodology because it relates to other property, private loan or overdraft debt), we estimate holders of only revealed debt explain 7.4pp of the net change (Table 16). This contribution is driven in the main by new participants who hold revealed credit card debt only.

Table 16. Breakdown of the aggregate change in debt before revealed debt removed, 2020 (percentage points)

	New participant				No longer a participant	Net change
	New only	*Revealed only*	*New & revealed only*	*Any unclassified**		
2020 (incl. revealed)	6.8	7.4	2.5	3.2	-4.7	15.1
2020 (excl. revealed)	6.8	-	2.5	3.2	-6.4	6.0

Source: HFCS panel (weighted to the 2018 population) and authors' own calculations.
Note: Unclassified debt = Other Property; Private Loan or Overdraft debt (all out of scope in our methodology). Missing field reflects revealed debt which has been removed.

Removing the revealed debt, debt participation in 2020 measures 58.6 per cent, still 6 percentage points higher than 2018 levels. A key driver for the participation remaining higher than 2018 levels is new NCL borrowing. Given our methodology may have over-identified some new and existing debt and a sizeable share of unclassified debt (namely other property or overdraft debt) could also be revealed, a net change of 6 percentage points likely represents an upper limit of the true change and this could diminish further – even to a negative net change – if all the *actual* revealed debt was removed.

6.2 Financial fragility measures

Excluding the revealed debt also has implications for interpreting financial fragility measures. Table 17 reports the values of five key ratios. Taken at face value (i.e. strictly comparing data from the 2018 HFCS exclusive of the CCR and 2020 HFCS inclusive of the CCR), four of the five ratios (debt service to income; debt to income; loan to value and mortgage debt service to income) improved. The only measure to show a deterioration was the debt to asset ratio which rose slightly from 22.1 to 22.6.

Had the CCR not been incorporated in 2020, our analysis suggests the debt to asset ratio would be essentially unchanged from 2018; the debt to income and debt servicing ratios would still have improved but not by as much, and the ratio of loan to value for HMR properties would show the same improvement as before. The impact of excluding the revealed debt on the servicing ratios is likely related to the excluded revealed balances typically being smaller.[19]

These changes emphasise the value of incorporating administrative debt data. Since the end of the financial crisis, many Irish households have deleveraged (Lydon and McIndoe-Calder, 2017), with this trend continuing into 2013-2018 (i.e. between the first and second waves of HFCS data for Ireland). As a result, the financial fragility measures improved over this period. For example, according to the ECB's full sample HFCS statistical tables, the median debt to income ratio in Ireland (excluding the CCR) fell from 102.1 in 2013 to 66.4 in 2018, while the mortgage debt service to income ratio declined from 15.7 to 13.0. Table 17 indicates further improvement between 2018 and 2020 but the CCR has helped to more accurately measure financial burden.

Table 17. Financial fragility measures, (median, %)

	2018 (excl. CCR)	**2020 (incl. CCR)**	**2020 (excl. revealed debt)**	**2020 (revealed debt holders)**
Debt service to income ratio	11.1	9.1	10.3	9.6
Debt to asset ratio	22.1	22.6	22.2	19.8
Debt to income ratio	71.4	49.3	50.4	57.5
Loan to value of HMR ratio	48.0	46.2	46.2	44.8
Mortgage debt service to income ratio	12.8	10.9	11.9	10.4

Source: HFCS panel (weighted to the 2018 population) and authors' own calculations.
Note: For purposes of defining debt servicing ratios under 2020 excluding revealed debt, wave 3 repayment amounts are carried forward to wave 4 unless debt is new or refinanced.

6.3 Distributional heterogeneity

Given our results show the extent of downward bias generated by misreporting can be large, it is useful to explore if this varies across the income distribution. Figure 11 presents the share of households in each income quintile with a different participation status or outstanding balance in 2020 once revealed debt is accounted for. For all debt types, the prevalence of misreporting is larger for balance than participation but there is generally limited variation across the distribution. This is particularly true for NCL debt.

[19] Though not shown, similar patterns are also found when separately conditioning on holding HMR mortgage debt and NCL debt.

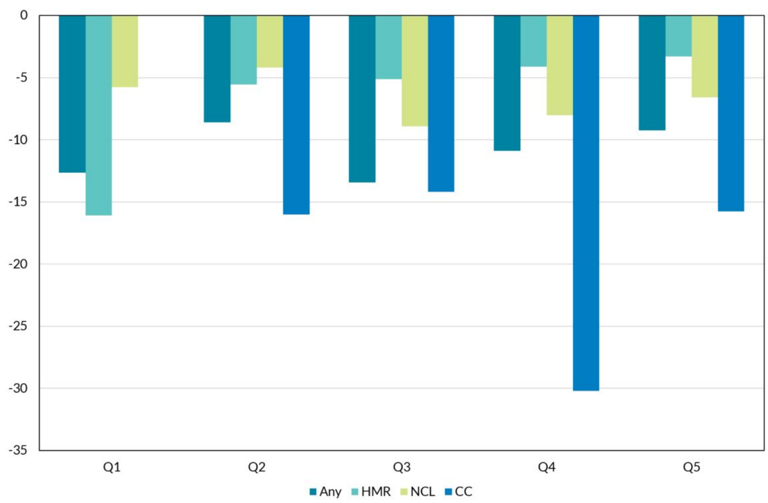
For HMR mortgage debt, households in lower income quintiles appear slightly more likely to have misreported their participation and balance. A U-shape pattern also starts to appear at the upper end of the distribution for credit card debt. However generally, measurement error seems to be a broad-based phenomenon, providing confidence that surveys remain an accurate source for distributional analysis.

Figure 12 considers the scale of misreporting by charting the average difference between balances in 2020, with and without revealed debt. All figures are negative, for all debt types and all income quintiles, further emphasising the widespread nature of under-reporting. On average, the scale of under-reporting (in percentage terms) is greatest for credit card debt, which peaks at -30.2 per cent for the fourth income quintile. While there does seem to be some variation in the extent of misreporting across the distribution, HMR debt is the only debt type to show any obvious trend. In this case, the under-reporting is greatest in the first quintile (-16.1 per cent) before improving up the distribution. However, the first quintile has the lowest HMR debt participation rate and therefore, the smaller number of observations could be driving some of the trend.

Figure 11: Share of households reporting a different balance and participation status in 2020 once revealed debt is accounted for, across the income distribution (%)

Source: HFCS panel (weighted to the 2018 population) and authors' own calculations.
Note: Charts are conditional on holding the specific debt type. Distribution reflects gross household income.

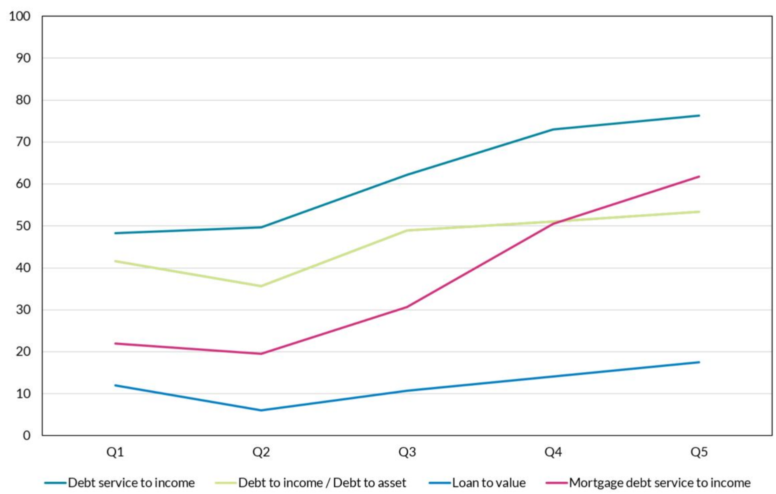
Figure 12: Average percent difference in balance in 2020 once revealed debt is accounted for, across the income distribution (%)



Source: HFCS panel (weighted to the 2018 population) and authors' own calculations.
Note: Charts are conditional on a household holding specific debt type. Average difference in credit card balance for first quintile suppressed for statistical disclosure purposes. Distribution reflects gross household income.

Finally in terms of the extent to which measurement error in financial fragility varies across the distribution, Figure 13 presents the share of households (by income quintile) with different values for several financial fragility measures in 2020 once revealed debt is accounted for. The prevalence of measurement error broadly increases up the distribution for all measures, consistent with both the ownership of debt and specifically any revealed debt increasing along the distribution. The difference is most notable for measures related to debt servicing, while it is more flat for loan to value.

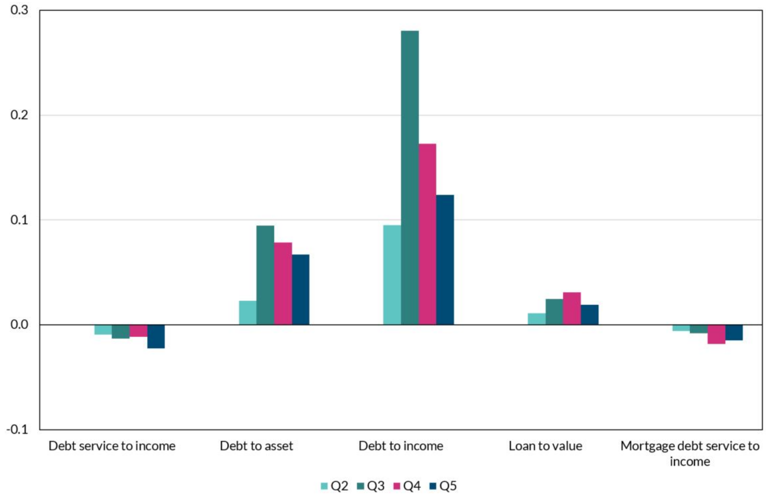
Figure 13: Share of households with a different financial fragility measure in 2020 once revealed debt is accounted for, across the income distribution (%)



Source: HFCS panel (weighted to the 2018 population) and authors' own calculations.
Note: Distribution reflects gross household income.

In terms of the size of the misreporting, the average percentage point difference after accounting for revealed debt is small (Figure 14). This is particularly the case for the debt servicing ratios, where it is negative. The slightly larger, positive differences for the remaining financial fragility measures indicate the average household experiences a minor deterioration in these ratios once revealed debt is accounted for.

Figure 14: Average difference in financial fragility measures in 2020 once revealed debt is accounted for, across the income distribution (percentage points)



Source: HFCS panel (weighted to the 2018 population) and authors' own calculations.
Note: Average difference for the first quintile suppressed for statistical disclosure purposes relating to the presence of zero and negative incomes in the first quintile and lower levels of debt participation. Distribution reflects gross household income.

7 Conclusion

In this paper, we use data from the panel households of the Irish HFCS to explore the extent to which the incorporation of the CCR has helped to improve both the *coverage* of household debt and the *quality* with which it is captured in the 2020 survey. Focusing on households' HMR mortgage, NCL and credit card debt, we carefully identify how much of each constitutes "new" borrowing since the last wave in 2018; an "existing" balance carried forward, or was previously not reported by the household but has now been "revealed" due to the inclusion of the CCR.

We estimate that supplementing survey responses with administrative data from the CCR has revealed debt worth €18.8bn (equivalent to around an eighth of the total value of outstanding debt in 2020). Ownership is widespread with at least one in three households holding revealed debt, rising to 47.6 per cent if conditioning only on debt holders. Credit card debt is found to have the highest share of revealed debt holders and as such, is a key driver of the increase in aggregate debt participation observed between waves.

The exposure of additional debt has important implications for our understanding of overall household indebtedness. Had the CCR not been incorporated, the HFCS data would continue to indicate that around half of Irish households hold debt as opposed to a true figure of over two-thirds. This greater prevalence of debt in the household sector than previously thought has real implications, including for unemployment and GDP (Mian et al., 2017), consumption (Mian et al., 2013; Ji et al., 2019) and saving (Bouis 2021).

There are three main takeaways from our analysis. First, households have a tendency to under-report their indebtedness, with the downward bias greater for outstanding balance than participation. However, we do not find significant differences in the extent of the bias across the distribution, implying that while survey data can be improved in level terms, it remains a useful source for distributional analysis. Second, there is heterogeneity in the measurement error across debt types. For example, we estimate the self-reported values for HMR mortgage debt underestimate the outstanding balance for this debt type by 14 per cent, rising to 38 per cent for NCLs and 64 per cent for credit card debt. Third, the inclusion of administrative data not only improves debt coverage but also how loans are characterised, with households with more complex balance sheets (not just in terms of quantity but more importantly, the variety of items to be reported) more likely to benefit from the inclusion of the CCR.

This final takeaway could lend support to the theory that misreporting is driven by rational inattention (i.e. households perceiving the costs of acquiring or updating their information to be more costly than the associated benefits). However, the finding could also underpin the relevance of behavioural economics. The initial errors in self-reported responses could arise unintentionally, for example because respondents suffer recall bias. The quality of their responses may be impacted by fatigue or a lack of trust in the interviewer. Some debts may be more salient than others, while respondents may also feel pressure to understate their debts in order to conform to social expectations. Our findings cannot confirm the exact drivers of the misreporting but they do suggest administrative data can reduce the problem. It is also important to remain aware that these biases exist and have consequences. Households with less accurate knowledge of their debt holdings may have lower debt literacy levels and make poorer financial decisions. For example, McGowan, Papadopoulos and Lunn (2023), note that if a household cannot recall the details of their loan, they may fail to consider switching to a better mortgage deal. Further research into understanding household financial decision-making and how better consumer outcomes can be achieved would be beneficial.

A key contribution of this paper is to document how a simple approach using panel data can be effective at estimating measurement error but it is important to recognise the limitations of our analysis. We have incomplete information on certain types of debt, meaning some of our categorisation rules rely on assumptions and there are cases where revealed debt is known to be under or overstated as a result. It is particularly difficult to identify where the CCR corrects a household's debt balance to be lower than the one self-reported. Accounting for this and the debt types not considered in this paper (overdrafts and other property debt), we would expect the ownership of revealed debt to be potentially much higher than our estimate. Finally, in the absence of formal longitudinal weights, we apply adjusted cross-sectional weights, but differences remain between the panel and the full sample and our estimates for outstanding balance (particularly for 2020) are sensitive to how the weights are designed.

Nevertheless, the findings will be of interest to policy makers, survey designers and researchers. Those who use survey data should understand the potential inaccuracies in self-reported responses and the complications this can pose for statistical inference. Survey designers may wish to explore incorporating additional administrative data or modifying their survey to improve the quality of data collection. Researchers should be aware of the improved accuracy and quality of the liabilities data in the Irish HFCS, which enables indebtedness and financial fragility to be more precisely measured across the distribution and over time. This will enhance the quality of studies focused on household indebtedness and decision-making. For example, in understanding why households use credit; how access to credit influences responses to an income shock and the consequences of changes in a household's debt burden.

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Appendix

Table A.1 Comparison of panel and full sample income, wealth and debt characteristics, 2018 and 2020

	Full Sample		**Panel Sample**	
	2018	**2020**	**2018**	**2020**
Gross household income (median, €)	47,971	52,700	49,517	52,600
Net wealth (median, €)	179,917	193,455	196,868	216,897
Any debt (%)	51.8	68.1	52.5	67.7
Any HMR mortgage debt (%)	26.1	30.4	26.7	31.5
Any NCL debt (%)	28.5	43.9	28.6	42.8
Any credit card debt (%)	12.7	26.8	14.0	27.2
Total debt (billions, €)	117.0	127.6	120.8	142.7
Total HMR mortgage debt (billions, €)	83.1	86.8	86.7	101.9
Total NCL debt (billions, €)	9.0	10.5	10.9	11.3
Total credit card debt (billions, €)	0.5	1.0	0.5	1.0
Median debt (€)	46,000	25,339	53,000	29,364
Median HMR mortgage debt (€)	125,000	124,253	128,000	128,081
Median NCL debt (€)	6,000	7,383	6,700	7,027
Median credit card debt (€)	1300	729	1,200	800

Source: HFCS; Full sample = 4,793 households in 2018 and 6,020 households in 2020. Panel sample = 2,808 HHs in each wave.
Note: For the full sample, respective cross-sectional weights are used in each wave. Whereas in the panel, adjusted 2018 cross-sectional weights have been applied to both waves. Variables rounded up to nearest euro where necessary.[20]

[20]We did consider using 2020 instead as these weights have underwent a more detailed calibration, including with additional variables such as the number of hectares of land farmed by region. However, they did not perform as well as 2018 in terms of correctly capturing the trend in debt participation. We determined this to be important as we are interested in understanding how the revealed debt contributed to changes in household indebtedness, and choosing which weights to use ultimately depends on the aims of the research.

Table A.2 Comparison of panel and full sample income, wealth and debt characteristics, 2018 and 2020

	Full sample 2018	2020	Panel HHs 2018	2020
Female	56.1	53.1	56.1	58.2
Age				
20-39	26.4	22.8	25.3	20.1
40-49	21.8	21.8	21.9	22.2
50-59	18.6	20.5	19.2	21.2
60-69	16.0	15.6	16.3	15.9
>70	17.2	19.3	17.3	20.6
Average (years)	51.9	53.3	52.2	54.3
Own their home	68.8	69.6	71.9	74.7
Principle economic status				
Employed	46.5	46.7	47.1	46.8
Self-employed	9.5	8.4	9.8	7.7
Unemployed	5.4	6.5	5.3	5.5
Retired	21.7	23.6	23.0	25.4
Other inactive	16.9	14.7	14.9	14.6
Education				
Primary	14.8	12.5	13.9	12.0
Secondary	41.8	41.9	40.3	41.0
Tertiary	43.4	45.6	45.8	47.0
Gross income				
Q1	20.1	20.0	20.2	20.1
Q2	20.0	20.1	19.9	20.0
Q3	19.9	20.0	20.0	20.2
Q4	20.0	20.0	19.9	19.9
Q5	20.0	20.0	20.0	19.8
Median (€)	47,971	52,700	49,517	52,600
Net wealth				
Q1	20.0	20.1	20.0	20.1
Q2	20.0	20.0	20.0	19.9
Q3	20.0	20.0	20.0	20.0
Q4	20.0	20.0	20.0	20.0
Q5	19.9	20.0	19.9	20.0
Median (€)	179,917	193,455	196,868	216,897
Debt service to income > 30% (%)	9.4	7.3	8.3	8.0
Number of debts	0.96	1.52	0.99	1.51
Balance sheet complexity †				
Low	38.5	27.5	33.8	24.3
Moderate	30.3	33.5	31.5	33.8
High	31.1	39.0	34.7	41.8

Source: HFCS and authors' calculations. Full sample = 4,793 households in 2018 and 6,020 households in 2020. Panel sample = 2,808 HHs in each wave.
Note: Full sample has been weighted according to respective cross-sectional weights. Panel sample weighted with 2018 weights adjusted for gender, age, income and debt participation differences. Any discrepancies due to rounding.
† Balance sheet complexity defined as number of different types of balance sheet items. Low = 6 or fewer; Moderate = between 7 and 8 and High = 9 or more.

Table A.3 Robustness check – Using alternative balance sheet complexity measures

	1	2	3	4	5
Female	-0.0373	-0.0239	-0.0346	-0.0562*	-0.0381
	(-1.43)	(-0.88)	(-1.11)	(-2.07)	(-1.44)
Age	0.0176*	0.0171*	0.00877	0.0113	0.0153*
	(2.53)	(2.48)	(1.19)	(1.40)	(2.25)
Age squared	-0.000158**	-0.000174**	-0.000103	-0.0000903	-0.000153*
	(-2.60)	(-2.90)	(-1.67)	(-1.34)	(-2.55)
Highest Education Level: Secondary	0.0728*	0.0802*	0.0697	0.0890*	0.0559
	(2.03)	(2.40)	(1.89)	(2.51)	(1.56)
Highest Education Level: Tertiary	0.0924*	0.139***	0.107**	0.110**	0.0940*
	(2.29)	(3.57)	(2.63)	(2.78)	(2.30)
Own home	0.0337	0.108*	0.0982	0.0461	0.0594
	(0.64)	(2.30)	(1.81)	(0.74)	(1.17)
Work Status – Self-employed	-0.112**	-0.0499	-0.066	-0.0718	-0.129***
	(-3.18)	(-1.22)	(-1.53)	(-1.62)	(-3.70)
Work Status – Unemployed	0.0365	-0.0109	-0.0548	0.0661	0.00902
	(0.60)	(-0.14)	(-0.55)	(0.83)	(0.16)
Work Status – Retired	0.0685	0.0914	0.0972	0.0709	0.0897
	(1.26)	(1.61)	(1.76)	(1.34)	(1.53)
Work Status – Other inactive	0.0683	0.0612	0.0686	0.071	0.052
	(1.58)	(1.43)	(1.42)	(1.34)	(1.19)
Income – 2nd Quintile	-0.027	-0.0151	-0.0582	-0.0117	-0.043
	(-0.71)	(-0.40)	(-1.35)	(-0.30)	(-1.07)
Income – 3rd Quintile	0.0863*	0.125**	0.0728	0.0960*	0.0624
	(2.00)	(3.02)	(1.66)	(2.07)	(1.35)
Income – 4th Quintile	0.0167	0.0488	-0.0381	0.0081	-0.0397
	(0.36)	(1.09)	(-0.80)	(0.17)	(-0.82)
Income –5th Quintile	0.0316	0.0499	-0.0366	0.0113	-0.0535
	(0.62)	(1.01)	(-0.71)	(0.22)	(-1.02)
Wealth - 2nd Quintile	-0.0751	0.0448	0.0708	-0.0152	-0.0361
	(-1.21)	(0.91)	(1.25)	(-0.22)	(-0.60)
Wealth - 3rd Quintile	-0.158*	0.0193	0.0362	-0.0697	-0.112
	(-2.32)	(0.35)	(0.57)	(-0.92)	(-1.69)
Wealth - 4th Quintile	-0.179*	0.0596	0.104	-0.000354	-0.118
	(-2.51)	(1.01)	(1.59)	(-0.00)	(-1.70)
Wealth - 5th Quintile	-0.244***	0.0938	0.101	-0.0263	-0.197**
	(-3.40)	(1.41)	(1.35)	(-0.31)	(-2.78)
Holds any new debt	-0.0821**	-0.158***	-0.319***	-0.346***	-0.105***
	(-3.14)	(-5.15)	(-8.90)	(-11.72)	(-4.04)
Holds any existing debt	0.0205	-0.0149	-0.167***	-0.251***	0.035
	(0.64)	(-0.40)	(-3.79)	(-7.12)	(1.10)
No. of types of balance sheet items	0.110***				
	(12.30)				
No. of loans		0.151***			
		(6.72)			
No. of debts			0.268***		
			(8.08)		
No. of types of debt				0.457***	
				(15.39)	
No. of balance sheet items					0.0846***
					(11.65)
Observations	14,040	14,040	14,040	14,040	14,040

Source: HFCS panel (weighted to the 2018 population) and authors' own calculations.
Note: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1
Results based on a logit estimation for likelihood of holding any revealed debt in 2020. Panel weights applied and all five implicates used, with standard errors clustered at the household level.
Reference category for education level= primary; for work status = employed; for income and wealth = 1st quintile.

Table A.4 Robustness check – Individual debt types

	1 Any revealed HMR debt	2 Any revealed NCL debt	3 Any revealed CC debt
Female	-0.00256	-0.0241	-0.0137
	(-0.25)	(-1.85)	(-0.74)
Age	0.0143***	-0.00128	0.0165***
	(3.38)	(-0.40)	(3.29)
Age squared	-0.000153***	0.0000023	-0.000129**
	(-3.77)	(0.08)	(-2.87)
Highest Education Level: Secondary	0.0229	0.000215	0.0286
	(0.95)	(0.01)	(1.18)
Highest Education Level: Tertiary	0.00632	-0.0215	0.0885**
	(0.26)	(-0.93)	(3.15)
Own home		-0.0291	-0.065
		(-1.04)	(-1.63)
Work Status – Self-employed	0.0214	0.00133	-0.0599**
	(0.99)	(0.09)	(-2.70)
Work Status – Unemployed	-0.0482**	0.0238	0.012
	(-2.67)	(0.90)	(0.29)
Work Status – Retired	-0.0348	0.0837	0.0584
	(-1.60)	(1.65)	(1.28)
Work Status – Other inactive	0.00932	0.0496*	0.00554
	(0.48)	(2.54)	(0.20)
Income – 2nd Quintile	-0.0452	-0.00922	0.0153
	(-1.82)	(-0.50)	(0.64)
Income – 3rd Quintile	-0.0267	0.0224	0.0756**
	(-1.03)	(1.03)	(2.68)
Income – 4th Quintile	-0.0288	0.0284	0.0654*
	(-1.09)	(1.05)	(2.08)
Income –5th Quintile	-0.00906	0.0041	0.0825*
	(-0.32)	(0.17)	(2.49)
Wealth - 2nd Quintile	-0.0842	-0.039	0.0166
	(-1.25)	(-1.33)	(0.50)
Wealth - 3rd Quintile	-0.112	-0.0608	0.0171
	(-1.65)	(-1.86)	(0.47)
Wealth - 4th Quintile	-0.121	-0.0793*	0.0135
	(-1.77)	(-2.49)	(0.34)
Wealth - 5th Quintile	-0.142*	-0.0721*	0.0251
	(-2.07)	(-2.08)	(0.61)
Holds any new debt	0.000272	-0.0243*	-0.0136
	(0.03)	(-2.13)	(-0.76)
Holds any existing debt	-0.0138	0.110***	0.0337
	(-1.16)	(4.26)	(1.45)
Balance sheet complexity – Moderate	0.0331*	0.0386**	0.0921***
	(2.55)	(3.16)	(5.82)
Balance sheet complexity – High	0.0697***	0.0893***	0.273***
	(3.98)	(4.76)	(9.23)
Observations	11,445	14,040	14,040

Source: HFCS panel (weighted to the 2018 population) and authors' own calculations.
Note: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1
Results based on a logit estimation for likelihood of holding any revealed debt for the given debt type in 2020. Panel weights applied and all five implicates used, with standard errors clustered at the household level. Reduced number of observations for model in Column 1 relates to the exclusion of renters from the sample as they are not eligible to hold HMR mortgage debt.
Balance sheet complexity defined as number of different types of balance sheet items. Low = 4 or fewer; Moderate = either 5 or 6, and High = 7 or more.
Reference category for education level= primary; for work status = employed; for income and wealth = 1st quintile and for balance sheet complexity = low. Home-ownership control excluded from regression relating to any revealed HMR mortgage debt.

Table A.5 Robustness check – Using different thresholds for low, moderate or high balance sheet complexity

	1	2
Female	-0.0271	-0.0349
	(-1.06)	(-1.32)
Age	0.0180*	0.0202**
	(2.54)	(2.79)
Age squared	-0.000163**	-0.000194**
	(-2.62)	(-3.06)
Highest Education Level: Secondary	0.0836*	0.0824*
	(2.29)	(2.41)
Highest Education Level: Tertiary	0.109**	0.119**
	(2.69)	(3.04)
Own home	0.0355	0.0908
	(0.67)	(1.83)
Work Status – Self-employed	-0.0799*	-0.0728
	(-2.31)	(-1.92)
Work Status – Unemployed	0.0375	0.0192
	(0.63)	(0.33)
Work Status – Retired	0.0779	0.092
	(1.35)	(1.65)
Work Status – Other inactive	0.0651	0.0696
	(1.48)	(1.67)
Income – 2nd Quintile	-0.0136	0.00135
	(-0.36)	(0.04)
Income – 3rd Quintile	0.107*	0.127**
	(2.43)	(3.08)
Income – 4th Quintile	0.0374	0.0662
	(0.79)	(1.40)
Income –5th Quintile	0.0485	0.084
	(0.97)	(1.67)
Wealth - 2nd Quintile	-0.0549	-0.00248
	(-0.89)	(-0.04)
Wealth - 3rd Quintile	-0.125	-0.0636
	(-1.88)	(-1.02)
Wealth - 4th Quintile	-0.136*	-0.0733
	(-1.96)	(-1.11)
Wealth - 5th Quintile	-0.174*	-0.0995
	(-2.43)	(-1.47)
Holds any new debt	-0.0658**	-0.0356
	(-2.62)	(-1.31)
Holds any existing debt	0.0515	0.0765*
	(1.57)	(2.29)
Balance sheet complexity – Moderate	0.242***	0.205***
	(8.09)	(5.84)
Balance sheet complexity – High	0.498***	0.380***
	(12.62)	(8.26)
N	14,040	14,040

Source: HFCS panel (weighted to the 2018 population) and authors' own calculations.
Note: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1
Results based on a logit estimation for likelihood of holding any revealed debt in 2020. Panel weights applied and all five implicates used, with standard errors clustered at the household level.
Reference category for education level= primary; for work status = employed; for income and wealth = 1st quintile and for balance sheet complexity = low.
Balance sheet complexity defined as number of different types of balance sheet items, with the thresholds set as follows:
Column 1: Low = 5 or fewer; Moderate =either 6 or 7, and High = 8 or more.
Column 2: Low = 6 or fewer; Moderate = either 7 or 8, and High = 9 or more.

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