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Some defaults are deeper than others: Understanding long-term mortgage arrears

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ABSTRACT

The 2007–2008 financial crisis yielded a significant number of delinquent mortgage loans, which ordinarily would have faced foreclosure and repossession. However, given the negative externalities of repossession, policy response has shifted towards forbearance and mortgage modification, which has led to longer spells in default for delinquent mortgage holders. It is therefore imperative to move beyond binary models of default towards an understanding of the factors that drive the depth of default spells. Exploiting a highly detailed dataset on financially distressed households in Ireland in 2012 and 2013, we are able to identify the impact of a range of *current* household-level factors, generally not available in loan-level studies of mortgage default, on the probability of entering early and deep states of mortgage default. Our results suggest that high loan-to-value ratios, consumer credit growth, shocks to mortgage affordability and unemployment should all trigger serious concerns among policy makers regarding subsequent stability in the mortgage market, with these measures all shown to have differentially large impacts on entry to deep, relative to early-stage arrears.

1. Introduction

The importance of the mortgage market to the banking system[1] and the economy at large cannot be overstated given the central role played by misguided mortgage lending in precipitating the 2007–2008 financial crisis. The fallout from this crisis was a tranche of borrowers with unaffordable loans. Globally, governments have responded through intervention, for example the Home Affordable Modification Program (HAMP) introduced in the US, which aimed to minimize the negative externalities associated with foreclosure (Campbell et al., 2011; Guiso et al., 2013 and Mian et al., 2011), and the Central Bank of Ireland's Mortgage Arrears Resolution Targets (MART) program. Remarkably, while there is a large stock of literature investigating the causes of default, there is scant empirical evidence on the extent to which the group of defaulted borrowers are heterogeneous in their responses to equity and affordability shocks. An understanding of these differences is of vital importance in evaluating the likely effectiveness of modification policies such as HAMP and MART, and in identifying patterns that should trigger concerns for potential repayment difficulties in the mortgage market.

In this paper we move beyond the typical binary treatment of mortgage default to consider deeper levels of mortgage default as distinct states.[2] Specifically, in our baseline model we take a sample of roughly twenty thousand financially distressed households in Ireland, and model the probability of default (greater than three missed payments, or ninety days past due) and deep default (greater than twelve missed payments, or three hundred and sixty days past due) relative to the probability of being in the early stages of mortgage arrears. We show that our results are not simply explained by the duration since the onset of a negative economic shock, but that our explanatory factors capture the ability and willingness of households to repay their mortgage.

The results of our baseline model suggest that households experiencing an unemployment shock or a divorce have a three and two percentage point higher probability of deep default, respectively.[3] We show that the affordability of a mortgage is a crucial

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[1] Jorda et al. (2014) have shown that the relative importance of mortgage lending in the activity of retail banks has increased unrelentingly since the 1950s, to the point where mortgages represent the majority of bank lending in most developed economies.

[2] See Table A.1 for a classification of the ways in which default is defined in the economics literature.

[3] The baseline probabilities of default and deep default in the estimation sample are 18% and 16%, respectively.

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determinant of deep mortgage defaults, with a one-standard-deviation increase in the monthly debt service ratio (DSR, measured as the ratio of mortgage repayment to net income) leading to a two percentage point increase in the probability of deep default. However, we extend the literature's understanding of the role of affordability in mortgage default by showing that it is the *shock* to mortgage affordability which is the most important factor: when the change in DSR between origination and our sample period is included, it is this affordability shock which drives entry to deep default, while the level of the DSR loses its statistical significance.

Borrowers' non-mortgage leverage is also shown to play an extremely important role in driving long-term mortgage distress, with a one-standard-deviation increase in non-mortgage debts (either measured as a ratio relative to total debts or relative to income) leading to an increase of between 1 and 3 percentage points in the probability of deep default. Lower household incomes are also shown to have explanatory power in the deep default equation. Further, higher mortgage interest rates are also shown to be associated with higher probabilities of both default and deep default. These findings provide a crucial insight for policy-makers both in non-crisis times and when designing responses to a mortgage arrears crisis: shocks to borrowers' ability to repay are crucial drivers of mortgage arrears, and are more likely to lead borrowers to deeper states of default, where any recovery to full repayments is extremely unlikely.[4]

In our baseline model, we find that housing equity has a similar impact on the depth of mortgage default to a household unemployment shock. Recent studies from Gerardi et al. (2013), Guiso et al. (2013) and Bhutta et al. (2010) suggest that affordability shocks such as unemployment and income shocks are the economically more important factor in explaining mortgage default, with extremely large falls in housing equity required before "strategic default" becomes likely.[5] Our finding suggests that the "double trigger" hypothesis appears to hold when considering long-term mortgage arrears during the Irish crisis, with both equity and affordability problems playing a role.

The post-2008 economic and policy climate in Ireland provides an ideal environment for a study that differentiates mortgage defaults according to their depth of arrears. Firstly, the sheer scale of the mortgage arrears crisis has few historical precedents, with the number of accounts in arrears rising from roughly 50,000 to 150,000 between 2009 and 2013, with the peak level representing 18% of all primary residential mortgages (Fig. 1a). Further, and more importantly from the point of view of this study, the composition of households in mortgage arrears has shifted through the crisis, with half of all accounts in arrears being in arrears of greater than one year (deep default) by end-2013 (Fig. 1b).

This build-up in the number of mortgages in deep default has been caused in part by the significant policy uncertainty that existed in Ireland between 2009 and 2013. A legal judgment passed in 2009 rendered the repossession of homes in default extremely difficult, with the legal uncertainty only fully eradicated in 2013. Further, due to the scale of the crisis in Irish banks and public finances, and the state's role in recapitalizing the country's main mortgage lenders, the period was characterized by a high degree of uncertainty around the likely debt write-downs that might be received by distressed mortgage borrowers. These policy and political factors led to a situation where properties entered deeper states of mortgage arrears, with no move toward repossession on the part of lenders. It is highly likely that in jurisdictions with more clarity around the foreclosure process, a large number of these properties would have been repossessed, thus exiting the system and placing downward pressure on the aggregate number of accounts in arrears.

The distinction between deep and early mortgage default has a number of crucial policy dimensions. Kelly and OMalley (2016) and McCann (2014) have shown that the depth of mortgage arrears has an extremely strong negative association with the probability of loan cure (a return to full repayment). In the case of Ireland, Kelly and OMalley (2016) show that the probability of loan cure for loans in default of three months is more than four times larger than the probability for loans in default of twelve months. These diminished cure probabilities have a number of important implications. From a prudential perspective, lower cure probabilities, especially if coupled with house price falls must be met with higher estimates of Loss Given Default (LGD), and subsequently higher loan provisions (Qi and Xiaolong, 2009). Lower cure probabilities also have social implications through their analogue, which is a higher probability of entry to foreclosure for loans that are not successfully modified. Heightened foreclosures exert significant distress on the homeowners in question, have negative implications for house prices in the locality (Gerardi et al., 2012), affecting performance of other local area modifications (Been et al., 2013) and place pressure on the public finances through the provision of social housing for those experiencing foreclosure.

Our paper builds on recent work that has exploited data on *current*, rather than at-origination measures of affordability such as household unemployment and income (Gerardi et al., 2013; McCarthy, 2014). Our study distinguishes itself from this previous work both in the focus on the depth of mortgage arrears, and in the nature of the dataset under study: both studies mentioned use survey data of between one and two thousand households, while our data set, on the other hand, contains information on twenty thousand households, with this information verified and audited by lenders before being used to assess the obligor's suitability for a modified mortgage.

The paper proceeds as follows: Section 2 explains our data sources, Section 3 describes our empirical approach, Section 4 reports regression results, while Section 5 concludes.

2. Data

Two data sources are used to construct the file used in our baseline estimation. The first is the Central Bank of Ireland's Loan Level Data (LLD). These files contain information on all loans issued by Irish banks participating in the 2011 Financial Measures Programme (FMP). In the case of the Irish residential mortgage market, these lenders account for roughly two thirds of the total market, making this a particularly rich source of data. The data have been explained in detail by Kennedy and McIndoe-Calder (2012) and used subsequently in a number of mortgage default analyses (Kelly, 2011; Kelly et al., 2014; Lydon and McCarthy, 2013; McCarthy, 2014). The data are concerned mainly with the terms of the *mortgages*, with reliable information on *inter alia* current mortgage balance, bank, current interest rate, interest rate type, origination and maturity dates, current loan to value ratio (LTV), First Time Buyer status (FTB), and property values at origination and at December 2013. Certain characteristics of the *borrower* are also reported in the data, such as marital status, geographic location, employment group, income and joint versus single assessment. These variables are all collected at the mortgage origination date.

As is the case in the majority of studies on mortgage default, the LLD suffers from an important omitted variable problem, given that *current borrower characteristics* are relatively scarce in the data. This problem arises from the fact that, in managing their mortgage

[4] Internal Central Bank of Ireland research shows that when borrowers have entered into arrears of greater than one year, the probability of any repayment is below 20%, and falls even lower once borrowers enter arrears of more than two years.

[5] Strategic default is generally considered to be a default that is explained by a loan amount that is larger than the market value of the property (referred to as negative equity, where the loan to value ratio rises above 100%).

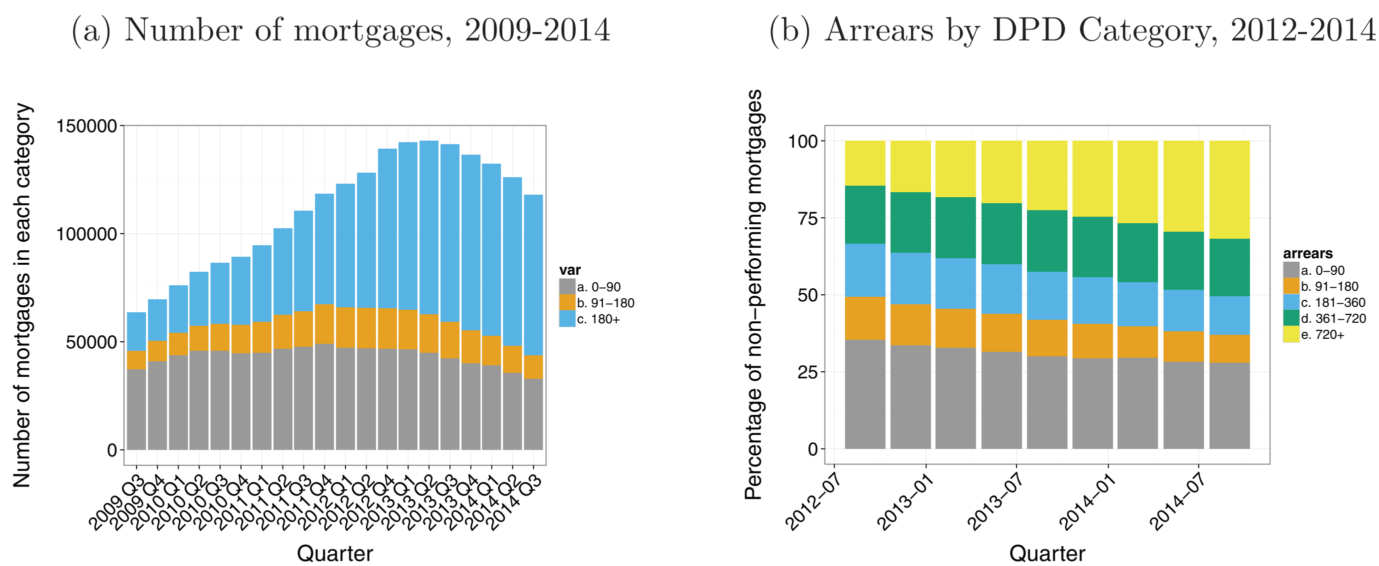

Fig. 1. The evolution of Irish mortgage arrears, 2009–2014. Market size: 760k primary residence mortgages. *Source:* Central Bank of Ireland; Residential Mortgage Arrears and Repossessions Statistics.

portfolios, lenders generally collect a large amount of information on borrowers at origination in order to inform the credit allocation decision, but do not follow up in detail on the borrowers' circumstances throughout the lifetime of the loan. This leads to an information gap, whereby most studies of mortgage default do not contain current information on factors as fundamental to the default decision as current employment status, income, indebtedness/leverage, household composition or marital status. Many studies of mortgage default proxy the "labor market" or "affordability" side of the mortgage default decision using regional economic conditions. Such an approach has been shown by Gyourko and Tracy (2014) to lead to a significant downward bias in the estimate of the effect of individual labor market outcomes on mortgage default.

In order to circumvent the information problems associated with the usage of data that focus mainly on loan and originating borrower characteristics, we exploit the Standard Financial Statement (SFS), a highly detailed data source on distressed borrowers. The completion of an SFS has been mandatory for any borrower engaging with their lender with a view to securing a modification to their mortgage terms since 2012. In order to form the basis of an assessment of the borrower's debt sustainability, the SFS captures information on *inter alia* non-mortgage debt exposures, employment status, income, expenditure patterns, household composition and marital status. Using a unique loan identifier, SFS files can be linked to the associated mortgages in the LLD, meaning that an extremely rich data set on current loan and borrower information can be constructed for 21,086 mortgages.

The timing of the introduction of the SFS coincides, but is not directly linked to, the introduction of the Central Bank of Ireland's MART programme, which began in 2013. This latter programme detailed quantitative targets for the number and the sustainability of mortgage modifications offered to distressed borrowers by domestic Irish lenders. It was introduced to address the perceived slow pace of resolution of the mortgage arrears crisis in Ireland. The SFS, on the other hand, was introduced at an earlier date in 2011 as a template for information inputting into the mortgage renegotiation process. The data suggest that the majority of households engaging with the mortgage renegotiation process in Ireland had in fact filled out an SFS for the first time before the introduction of the MART programme in early 2013 (Table 2 gives quarter-by-quarter breakdown of the date of borrower engagement in our data). During the sample period, there were no formal guidelines around income thresholds or the "type" of borrower that should receive a modification; rather it was the position of policy-makers that lenders should assess each household's financial position on a case-by-case basis to ascertain how large of a monthly mortgage repayment could be afforded given the financial and demographic circumstances in question. Internal work from Central Bank of Ireland economists estimates that during the sample period, between 35 and 50% of all SFS entries resulted in a "permanent mortgage modification" being issued.[6]

The way in which the SFS data are collected presents two sources of bias. Firstly, given that by definition a borrower must be experiencing mortgage repayment difficulty before filling out an SFS with a bank, performing loans are hugely under-sampled in the SFS data. As a result, this dataset is not suited to the estimation of a standard default model where loans greater than 90 days past due are compared to those with no or early-stage arrears. However, where the purpose of the model is to understand the heterogeneity of defaulted borrowers and hence predict borrowers' entry into *deeper states* of mortgage default, the SFS provides a wealth of important household balance sheet information, unavailable at such a scale to any previous study of which we are aware.

The second source of bias in the SFS data relates to the fact that, in order for SFS information to be available, the borrower must by definition have engaged with their lender after having experienced a negative shock. Given the policy context during our sample period discussed in Section 1, it is entirely plausible that non-engaging borrowers are a non-random sample of the population. Borrowers who suffered the worst shocks, or who experienced the biggest deterioration in their housing equity position, may be those that are least likely to engage with their bank.

Table 1 provides some evidence on the extent of the bias. We compare loans with and without an SFS for loans in our three in-arrears categories, as well as across all loans in arrears. In making these comparisons, we are restricted to variables that are available for all loans in the LLD dataset. There are some differences between borrowers with and without an SFS. Borrowers who have filled out an SFS appear to have larger loans at December 2013,

[6] A "permanent" modification is defined as one that permanently alters the debt service burden of the borrower. Examples include arrears capitalization, term extension, split or "warehoused" mortgages where part of the principal is frozen until maturity.

Table 1
Comparison of loans with and without an SFS by arrears bucket.

Arrears Group	1–90	90–360	360+	All Arrears
Average LTV December 2013				
0	**85.37**	95.06	**106.89**	97.39
1	**88.06**	94.97	**104.18**	96.89
Average Balance				
0	**155,491**	**174,093**	**184,960**	**173,390**
1	**173,928**	**183,924**	**192,683**	**184,896**
Average Interest Rate				
0	**3.57**	**3.48**	**3.72**	**3.61**
1	**2.99**	**2.96**	**3.05**	**3**
Dublin Share				
0	**0.27**	**0.27**	**0.23**	**0.25**
1	**0.21**	**0.21**	**0.19**	**0.2**
Share of Trackers				
0	**0.36**	**0.37**	**0.38**	**0.37**
1	**0.48**	**0.51**	**0.49**	**0.49**
Share Self-Employed at Origination				
0	0.09	**0.11**	**0.14**	**0.12**
1	0.1	**0.12**	**0.17**	**0.14**
Share Married at Origination				
0	**0.48**	**0.47**	**0.45**	**0.47**
1	**0.61**	**0.58**	**0.54**	**0.57**
Average Age				
0	**44.85**	**45.21**	**46.05**	**45.47**
1	**46.86**	**46.39**	**46.71**	**46.63**
Average Income at Origination				
0	57661.06	58675.19	**61173.31**	59541.57
1	57714.25	58923.34	**59608.07**	58955.74
Share of First Time Buyers				
0	**0.41**	**0.41**	**0.39**	**0.4**
1	**0.26**	**0.26**	**0.26**	**0.26**
Loan Age (Months)				
0	**101.65**	**102.21**	**108.19**	**104.68**
1	**88.88**	**90.89**	**96.93**	**92.78**

0 indicates loans within each arrears category without an SFS; 1 analogously indicates those with an SFS.
Bold font implies that the group means are significantly different at the 5% level.

Table 2
Date of application, SFS data set.

Date	Count	Share	Cum. Share
Q1 2012	2909	13.8	13.8
Q2 2012	3599	17.07	30.8
Q3 2012	5209	24.7	55.5
Q4 2012	2914	13.82	69.4
Q1 2013	2408	11.42	80.8
Q2 2013	1912	9.07	89.9
Q3 2013	1619	7.68	97.6
Q4 2013	516	2.45	100
Total	21,086		

with this difference holding across all arrears buckets. Crucially however, these loan size differences are not reflected in differences in housing equity, with house valuations acting to offset these differences, leaving CLTV similar between the two groups (the average CLTV among non-engaged borrowers is 95.85 across all loans in arrears, while the average for those with an SFS is 97). Interest rates are lower among loans with an SFS, with this difference being driven by a higher share of tracker mortgages among those with an SFS (49 versus 34%). First-Time Buyers (FTB) are less prevalent among those filling out an SFS (26 versus 40%).

Concerns regarding differences such as those outlined above should be alleviated by the degree of similarity between the SFS and non-SFS groups. Loans with an SFS appear to be only slightly more likely to come from outside Dublin (25 versus 20%). Importantly, borrower income at origination and the share of self-employed borrowers (an *ex-ante* predictor of default as shown in Kelly et al. (2014) at origination appear to be close to identical in the SFS and non-SFS groups. Finally, the average age among SFS and non-SFS loans is 45.9 and 46.6 years, respectively. These similarities provide a layer of assurance that a model run using our sample provides a reasonable approximation of patterns across the population of distressed mortgages.

Whereas the LLD is a cross section of the full mortgage book of the four participating banks at December 2013, entries to the SFS data set vary in their timing. The SFS is filled out at the point of engagement between borrower and lender, with Table 2 reporting the distribution of SFS submission dates. 70% of our observed SFS entries are in the calendar year 2012.

2.1. Dependent variable

The distribution of the depth of mortgage arrears among the 21,086 mortgages available in the SFS and LLD data is reported in Table 3. As one would expect given the nature of the SFS data-gathering process, loans without any arrears are severely under-represented in the SFS data set (84 versus 48%). Given that the SFS data relates solely to mortgages in repayment difficulty, it is instructive to observe the share in each category *among those in arrears* across each data set. The columns $Share_{Arr}$ give the percentage of the non-zero *DPD* samples in each of our three arrears categories. Using this measurement, the SFS data appear to match much more closely the patterns observed in the LLD population data. The under-representation of deep default mortgages in the SFS sample (31.6 as opposed to 41.5%) suggests that those who engage with their lender by filling out an SFS are less likely to be in deep default.

It may seem surprising that such a large share of the SFS sample have engaged with a zero arrears balance. Such a pattern may be suggestive of strategic engagement on behalf of borrowers hoping to profit from the introduction of mortgage modifications, as evidenced in the US by Mayer et al. (2014). However, we believe that in the Irish context this is not a serious concern. Mortgage modifications were offered in the period under review on a case-by-case basis, where each household's balance sheet was subjected to intense scrutiny by the lender in order to ascertain what size of a monthly repayment could be shouldered by the household. The information inputting into this decision-making process was audited by the lender where possible, meaning that "strategic" borrowers hoping to lower their repayment burden as a result of the modification programme were unlikely to profit in cases where repayment reductions were not warranted by their financial situation.

In our baseline empirical model, we amalgamate all those mortgages with zero to ninety days past due into an "early distress" category. The intuition for this grouping is that any borrowers filling out the SFS with zero DPD are not "performing" in a similar way to the majority of zero-DPD borrowers in the full LLD population. Rather, these are borrowers who have pre-emptively engaged with their lender due to repayment difficulty. A three-category multinomial logit model is specified where the probability of being in default and deep default is modelled relative to the reference category "early distress".

Fig. 2a and b provide some context around the way in which loans transitioned between differing depths of mortgage arrears during the Irish crisis. Fig. 2a plots the percentage of loans at different starting DPD categories that have moved to an improved DPD state in the subsequent quarter. The chart shows clearly that recovery is very unlikely among loans in 360+ DPD, with the transition rates to an improved status being below 10% throughout the sample period 2011–2014. There is an intuitive pattern to the

Table 3
Dependent variable, LLD and SFS data sets.

		LLD			SFS		
Category	DPD	Count	Share	$Share_{Arr}$	Count	Share	$Share_{Arr}$
Performing	0	224,500	83.71		10,120	47.99	
Early Arrears	1–90	12,797	4.77	29.3	3541	16.79	32.3
Default	91–360	12,751	4.75	29.2	3955	18.76	36.1
Deep Default	> 360	18,141	6.76	41.5	3470	16.46	31.6
Total		268,189			21,086		

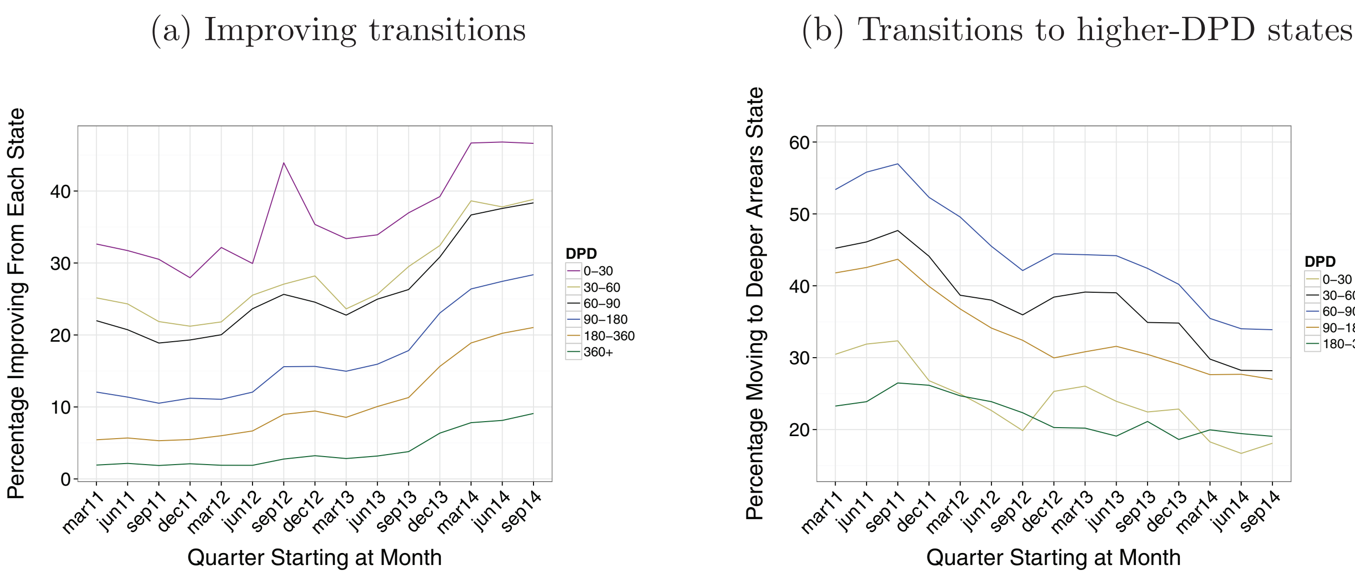

Fig. 2. One-quarter transitions between mortgage delinquency states, 2011–2014. *Source:* Central Bank of Ireland loan-level data.

data whereby these improving transitions are more likely among lower-DPD starting states; the transition rate among loans starting between 0–30 DPD is between 30 and 45% in each period, while the equivalent rate for those between 90–180 DPD is 10 to 25% in most quarters. The improving Irish economy and heightened implementation of mortgage modifications is evident in the data, with the transition rates growing over time for every starting state. Fig. 2b analogously plots the transition rate to *worsened* DPD states. The improving economic and financial environment is again evident for each starting state, with falls in each transition rate over time. The highest transition rate to a higher-DPD state is for loans between 60 and 90 DPD in each quarter.

3. Empirical framework

At the core of our framework is a latent variable Y^*, which is decreasing in the likelihood that a household will repay its monthly mortgage payment M_t. All households begin their life as mortgage holders with a Y_0^* that is consistent with a full monthly mortgage repayment. This condition is guaranteed to hold if we assume that banks' loan underwriting policies are such that all customers are given a mortgage that is consistent with repayment at origination, M_0. The empirically-observed dependent variable in our baseline model is the depth of arrears, *DPD* at the point of SFS engagement, T_{SFS}, which can take on three values (early distress, default and deep default). *DPD* rises by one month when a monthly repayment M_t is missed. However, *DPD* may also rise by some fraction F of one month when a household makes a partial payment $(1-F)^*M_t$.

Between loan origination and T_{SFS}, a series of economic shocks will affect all households to varying degrees. Our dependent variable *DPD* is the realization of Y^*, where Y^* can be influenced by:

1. The propensity of a household to be subject to a negative shock.
2. The nature of the shock.
3. The ability of the household to continue repayments, conditional on suffering a given shock.
4. The willingness of the household to continue with repayments.
5. The speed of engagement with the lender, once the household realizes that its debts are unaffordable.
6. The time elapsed between the onset of the negative shock and December 2013.

We contend that the depth of arrears at T_{SFS} will be influenced by explanatory factors that are related to some or all of the above factors. In our baseline model, where a wide range of current household information is available to us, it is easy to imagine that household net income, unemployment status, the size of non-mortgage debts, the monthly debt service ratio (DSR), and household composition are all proxies for factors (1), (2) and (3) above. These variables, along with a measure of the household's equity position, may also influence factors (4) and (5), which relate to the willingness to repay, and the speed of engagement with the lender.

Factor (5), the speed with which a borrower engages with her lender, may also potentially drive differences between otherwise identical borrowers. Consider two households that suffer an identical shock, at an identical time, with an identical ability to pay. Household 1 engages with their bank after having missed twelve repayments, and fills out an SFS with a $DPD = 360$. Household 2, on the other hand, decides to approach his lender after having missed six repayments, and therefore is recorded in our SFS model as having a $DPD = 180$.

The final factor (6) underlying Y^* is the duration since the negative shock. It is important to acknowledge that the nature of our dependent variable is such that two households who have

Table 4
Summary statistics, SFS sample.

Variable	Obs	Mean	Std. Dev.
FTB	21,086	0.26	0.44
Term (Months)	21,086	315.81	84.19
Adjusted CLTV	21,086	86.24	44.1
CLTV	21,086	92.42	45.8
Loan Age	21,086	92.31	30.59
Current Interest Rate	21,086	2.94	1.55
Borrower Age	21,086	38.31	8.71
Fixed Rate	21,086	0.05	0.21
SVR	21,086	0.45	0.50
Tracker	21,086	0.50	0.50
Net Monthly Income (€ 000)	21,086	2.88	1.56
Unemployment Shock	21,086	0.30	0.46
Divorced Since Origination	21,086	0.07	0.26
Debt Service Ratio (DSR)	21,086	0.33	0.28
Δ DSR	19,941	0.049	0.248
Other Debt to Income	21,086	2.60	6.42
Other Debt to Total Debt	21,086	0.20	0.24
Single, No Children	21,086	0.17	0.37
Single, 1/2 Children	21,086	0.10	0.30
Single, 3+ Children	21,086	0.02	0.15
Couple, No Children	21,086	0.18	0.38
Couple, 1/2 Children	21,086	0.34	0.47
Couple, 3+ Children	21,086	0.20	0.40

Table 5
Breakdown of key variables by arrears states, SFS sample.

	Early Distress	90–360	360+
Total	64.8	18.8	16.5
Non-FTB	64.7	18.6	16.7
FTB	65	19.2	15.8
Fixed	79.9	12.1	8.1
SVR	62.9	19.2	17.9
Tracker	65	19	16
No Divorce	65.6	18.6	15.9
Divorce Since Origination	54.6	21.3	24.1
No Unemployment	68.6	18.1	13.3
Unemployment Shock	56	20.2	23.8
Couple, no children	61.1	20.4	18.5
Couple 1/2	68.2	17.9	13.9
Couple 3+	64.7	19.7	15.6
Single, no children	65.6	17.3	17.1
Single 1/2	61.1	19	19.8
Single 3+	53.3	21.1	25.6
Mean values for continuous variables			
Borrower Age	38.4	37.9	38.3
Vintage (Months)	89.9	93.9	100.1
Opening Term (Months)	313.4	325.4	314.5
Net Monthly Income	3006	2811	2470
Adjusted CLTV	86.2	87.7	84.7
CLTV	89.0	97.6	101.8
DSR	0.304	0.347	0.42
Δ DSR	0.025	0.059	0.135
Interest Rate	2.9	2.99	3.06
Other Debts to Income	2.26	2.53	3.98
Other Debts to Total Debt	0.18	0.2	0.27

experienced an identical shock, and have an identical ability and willingness to repay, will have different *DPD* counts at T_{SFS}, depending on when the negative shock first affected the household. If the earlier onset of a shock is correlated with our household-level variables, for example because households in certain geographical areas or working in certain industrial sectors are more prone to negative shocks that hit specific sectors of the Irish economy at an earlier date, then the estimation of our multinomial model may be subject to omitted variable bias. Further, it may be that more financially vulnerable households have fewer resources available to withstand a shock and therefore enter arrears with greater frequency, for the same magnitude of shock, than those with greater savings or family resources to aid in continuing repayment.

For the reasons outlined above, we include the time, in calendar months, since a household first entered arrears as a control variable in our baseline models. This timing is directly observable due to the panel data nature of the LLD. If Time in Arrears, *TinA*, is controlled for, we contend that the remaining effect of the explanatory variables on *PD* and *PDD* can be solely attributed to factors (1) to (4) above, given that *TinA* captures both the time since initial shock (6), as well as acting as proxy for the willingness to engage (5). It should be noted that this estimation strategy is more onerous on the data than that typically employed in a binary default model, given that *TinA*, through its positive correlation with arrears balances, should be expected to reduce the explanatory power of the remaining specified variables.

Fig. 3 provides Kernel density plots of *TinA* for each of the three groups comprising our dependent variable. As would be expected, *TinA* is distributed further to the right for loans in deeper states of arrears. However, there is significant overlap in the *TinA* distributions across the three groups. This overlap suggests that there are many households who, by virtue of duration alone, should have entered the deep default state, but have either partially paid, or only missed payments sporadically since the onset of the shock. Our estimation strategy rigorously isolates the impact of the explanatory variables on the (in)ability of the household to resist the movement into deeper arrears once the negative shock has been experienced.

Fig. 4 provides a visual representation of how households may end up with differing *DPD* values in our estimations. Household types 1 and 2 differ only in the speed with which they decide to approach their bank. Household 3 has suffered a shock in early 2012, but has managed to pay half of the monthly repayment due in every month from then until T_{SFS}. This pattern suggests that this type of household varies crucially from households 1 and 2 in its ability to withstand the negative shock. The final type of household described in the schematic is one that, upon experiencing a shock, immediately approaches the lender to fill out an SFS. As shown in Table 3, this type of household accounts for two-fifths of all households filling out an SFS.

The net result of the staggered engagement with the SFS process is a dataset which takes the form of a pooled cross section, with DPD_i being the realization of the underlying propensity for

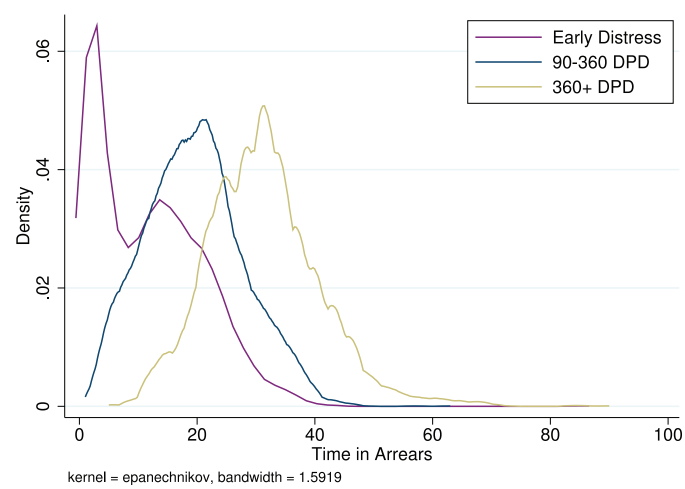

Fig. 3. Time in Arrears (months).

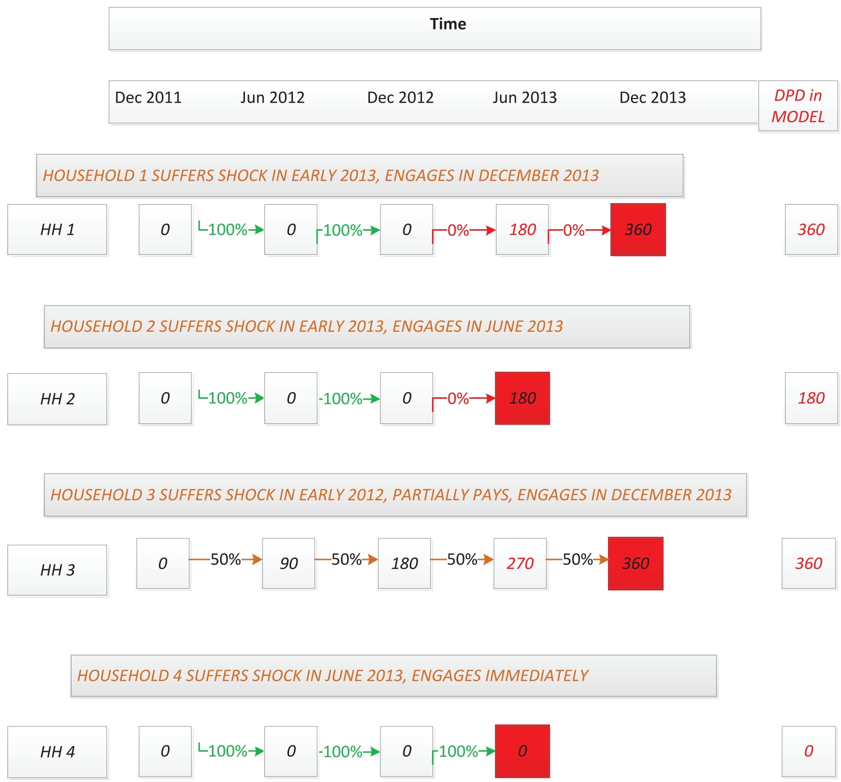

Fig. 4. Schematic of *DPD* accumulation process for example households.

delinquency level DPD_i^*, for loan i, which takes the values:

$$DPD_i = \begin{cases} 1 & 0 \le DPD_i^* < 90; \\ 2 & 90 \le DPD_i^* < 360; \\ 3 & DPD_i^* \ge 360 \end{cases}$$

In our baseline specification, the probability of the realized *DPD* indicator taking the value of 1 or 2 modeled as a function of the time in arrears and the underlying characteristics of the borrower, loan terms and dwelling controls:

$$Pr(DPD_i = 2|DPD_i = 3) = \mathbf{F}(TinA_i, \mathbf{X_i}, \mathbf{Z_i}) \quad (1)$$

where $\mathbf{X_i}$ is a vector of borrower-specific controls, $\mathbf{Z_i}$ a vector controls for loan characteristics. Table 4 reports summary statistics for $\mathbf{X_i}$ and $\mathbf{Z_i}$ for our baseline model sample.

The borrower-specific controls, $\mathbf{X_i}$, include first time buyer (FTB) status, borrower age modeled as a quadratic term and indicators for change in marital status, family composition and the current employment status of the borrower.[7] In the model sample, 7% of households have experienced a divorce since origination, while 30% of households are experiencing unemployment at the point of engagement T_{SFS}. The average age of the primary borrower is 38. Current income is captured in the SFS data by observing all sources of household income, whether from salaries, self-employed income or welfare payments. The average after-tax monthly household income in our sample is € 2872.

We measure mortgage affordability by the Debt Service Ratio (DSR), which is the ratio of monthly repayment to monthly net income with a sample average of 33%. Combining originating information and SFS information, we can construct a measure of the *shock* to affordability experienced by each household, which we refer to as Δ DSR. Such a combination of originating and current information provides an extremely useful indicator of mortgage distress which is rarely available to researchers in the area. The average increase in the DSR between origination and T_{SFS} is 4.9 percentage points.

Non-mortgage debts constitute all reported Buy-to-Let mortgage, credit card, credit union, consumer loan and business debt. We measure these "other debts" in two ways in our regression models: firstly as a share of total debt (with a mean value of 20%), and secondly as a ratio to annual household net income (with a mean value of 2.6 times). We calculate both these measures using the total outstanding value of other debts, rather than a monthly repayment, given that many forms of consumer debt do not have a term structure or an associated monthly repayment.

The set of loan-specific controls $\mathbf{Z_i}$ included in the model is comprehensive. The average term at origination is 316 months, average loan age at T_{SFS} is 92 months, while the average interest rate on loans is 294 basis points. The share of loans accounted for by the "tracker" (following the ECB reference rate with a fixed margin) is 50%, while a further 45% are Standard Variable Rate (SVR) mortgages.

Previous studies have taken as standard the inclusion of the Current Loan to Value Ratio (*CLTV*) as a measure of housing equity. However, as elaborated on in Kelly and McCann (2015), there is a mechanical reverse causality in the *DPD* – *CLTV* relationship that is ignored by most researchers in this area. This bias is driven by the fact that, once a mortgage borrower stops payment, their outstanding balance no longer reduces along the monthly amortization schedule, while all performing loans continue to amortize as per contract terms. To exacerbate the effect, any arrears balance accumulated is often capitalized and added to the outstanding

[7] Unemployment shocks are measured as occurring where at least one individual in the household is not working. In cases where adults are not working but not unemployed in the statistical sense (e.g. they may be students, retired or ill), they are coded as being unemployed to reduce the number of categories in the data, while retaining the economic information as to whether or not income is being earned in the household.

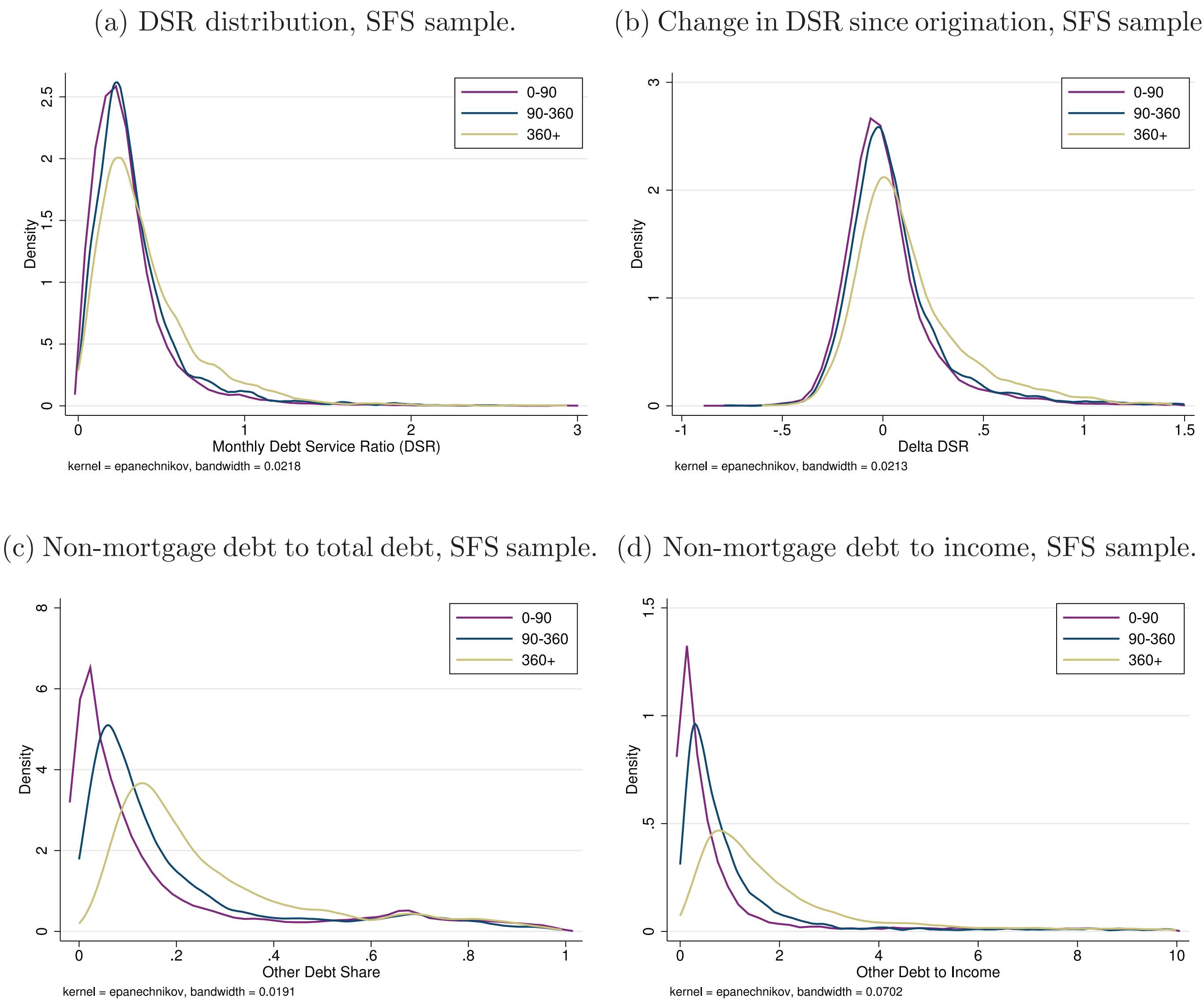

Fig. 5. Distributions across DPD states.

loan amount on the non-paying loans. This has the effect that the numerator in the *CLTV* will appear higher for non-paying loans in a cross-sectional regression setting, due mechanically to the fact that the loan is not paying. If not corrected for, this can lead to erroneous conclusions regarding the impact of housing equity on mortgage default. Due to this bias, we propose an alternate measure of housing equity which we term Adjusted *CLTV*, which adjusts downwards the observed CLTV values in the data set to account for the number of missed payments on defaulted loans.

Fig. 5 plots the distribution of four key explanatory variables across the three DPD categories comprising our dependent variable. Fig. 5a shows that the mean DSR value of 32% masks a long right tail, with extremely unaffordable mortgages with DSRs of greater than 100% being rare, but values up to 150% existing in the data. The distribution is skewed further to the right among those in deep default, suggesting a weaker affordability position is associated with long-term arrears. Fig. 5b shows that the distribution of DSR shocks for those in deep default sits clearly to the right of those in the other two groups.

The distribution of other debts as a share of total debts is plotted in Fig. 5c, with the plot showing that large shares of non-mortgage debt are relatively rare in the data set – most households' mortgages account for between 80 and 90% of their total debt burden. However, for households in deep default, there is a significantly larger share with non-mortgage debts accounting for 30–40% of their outstanding debts. Similarly, in Fig. 5d it is shown that most households have a non-mortgage debt value that is lower than one times their annual net income. Again, households in deep default are much more likely to have higher debt to income ratios, with ratios larger than two being relatively prevalent.

Table 5 reports tabulations and means for explanatory variables within each category of our dependent variable. Some important differences are clear in the raw data, with deeper-arrears mortgages being more prevalent among variable (SVR) and tracker mortgages than fixed-rate loans, among families experiencing a divorce since origination, and families with all or one adult not working. In terms of family structure, couples with one or two children have the lowest rates of deep default at 15.68%, with the highest rates among single people with three or more children, at 25.5%.

Analysis of the continuous explanatory variables reveals that monthly net income is shown to be over € 500 lower among

Table 6
Baseline regressions. Multinomial Logit Results. Average Marginal Effects Reported.

	(Model 1)		(Model 2)		(Model 3)		(Model 4)	
	(1) 90–360	(2) 360+	(3) 90–360	(4) 360+	(5) 90–360	(6) 360+	(7) 90–360	(8) 360+
Time in Arrears	0.00343***	0.0159***	0.00356***	0.0156***	0.00343***	0.0156***	0.00355***	0.0152***
	(0.000157)	(0.000187)	(0.000159)	(0.000188)	(0.000163)	(0.000194)	(0.000165)	(0.000195)
FTB	0.0133*	−0.0179***	0.0140**	−0.0153***	0.0136**	−0.0185***	0.0143**	−0.0159***
	(0.00683)	(0.00471)	(0.00684)	(0.00470)	(0.00682)	(0.00470)	(0.00683)	(0.00469)
Term	0.000118**	−0.0000976***	0.000106**	−0.0000573	0.000115**	−0.0000849**	0.000103**	−0.0000438
	(0.0000478)	(0.0000355)	(0.0000479)	(0.0000356)	(0.0000467)	(0.0000342)	(0.0000469)	(0.0000343)
SVR	0.0311**	0.0433***	0.0321**	0.0409***	0.0308**	0.0434***	0.0318**	0.0411***
	(0.0148)	(0.0117)	(0.0148)	(0.0116)	(0.0148)	(0.0118)	(0.0148)	(0.0117)
Tracker	0.0841***	0.127***	0.0858***	0.126***	0.0838***	0.126***	0.0855***	0.125***
	(0.0222)	(0.0160)	(0.0223)	(0.0160)	(0.0222)	(0.0160)	(0.0223)	(0.0161)
Curr Int Rate	0.0184***	0.0359***	0.0188***	0.0361***	0.0186***	0.0350***	0.0190***	0.0352***
	(0.00491)	(0.00383)	(0.00489)	(0.00380)	(0.00491)	(0.00384)	(0.00490)	(0.00381)
Adjusted CLTV	0.0000194	0.000639***	0.0000323	0.000657***				
	(0.0000870)	(0.0000654)	(0.0000866)	(0.0000645)				
CLTV					0.0000286	0.000604***	0.0000426	0.000618***
					(0.0000788)	(0.0000563)	(0.0000785)	(0.0000556)
Other Debt to Income	−0.000363	0.00219***			−0.000351	0.00217***		
	(0.000382)	(0.000252)			(0.000381)	(0.000251)		
Other Debt Share			−0.00431	0.110***			−0.00398	0.109***
			(0.0112)	(0.00786)			(0.0112)	(0.00786)
Monthly Net Income	−0.00131	−0.00286*	−0.00185	−0.00582***	−0.00115	−0.00330**	−0.00170	−0.00626***
	(0.00214)	(0.00164)	(0.00223)	(0.00168)	(0.00215)	(0.00164)	(0.00223)	(0.00169)
Divorced	0.0110	0.0175**	0.0102	0.0208***	0.0112	0.0173**	0.0103	0.0206***
	(0.00975)	(0.00683)	(0.00973)	(0.00682)	(0.00975)	(0.00682)	(0.00973)	(0.00681)
Unemployment Shock	−0.00571	0.0282***	−0.00553	0.0288***	−0.00581	0.0284***	−0.00562	0.0290***
	(0.00598)	(0.00434)	(0.00599)	(0.00432)	(0.00598)	(0.00433)	(0.00598)	(0.00431)
Debt Service Ratio	0.0258***	0.0333***	0.0234**	0.0399***	0.0267***	0.0308***	0.0243**	0.0373***
	(0.00956)	(0.00675)	(0.00948)	(0.00665)	(0.00957)	(0.00675)	(0.00949)	(0.00665)
Single, 1/2=1	0.00928	0.0129*	0.00960	0.0127*	0.00920	0.0130*	0.00954	0.0128*
	(0.00993)	(0.00721)	(0.00993)	(0.00714)	(0.00992)	(0.00719)	(0.00992)	(0.00713)
Single, 3+=1	0.0209	0.0219*	0.0223	0.0219*	0.0211	0.0219*	0.0224	0.0218*
	(0.0189)	(0.0118)	(0.0190)	(0.0118)	(0.0189)	(0.0118)	(0.0190)	(0.0118)
Couple, Zero=1	0.0184**	0.00741	0.0195**	0.00687	0.0182**	0.00756	0.0193**	0.00700
	(0.00896)	(0.00643)	(0.00897)	(0.00635)	(0.00896)	(0.00643)	(0.00896)	(0.00635)
Couple, 1/2=1	0.00565	−0.00381	0.00620	−0.00291	0.00556	−0.00364	0.00613	−0.00276
	(0.00803)	(0.00581)	(0.00804)	(0.00576)	(0.00803)	(0.00581)	(0.00803)	(0.00576)
Couple, 3+=1	0.0105	0.00373	0.0115	0.00456	0.0104	0.00406	0.0114	0.00486
	(0.00912)	(0.00649)	(0.00913)	(0.00643)	(0.00911)	(0.00649)	(0.00913)	(0.00643)
Observations	21,086	21,086	21,086	21,086	21,086	21,086	21,086	21,086

Controls for county, loan age (quadratic), borrower age (quadratic) and bank included in all models Robust standard errors in parentheses;
* $p < .1$.
** $p < .05$.
*** $p < .01$.

deep-default households than those in early distress. The DSR is 40.5% among deep-default mortgages, which differs importantly from early distress and early default mortgages (29.7 and 33.5%, respectively). The average Δ DSR is also vastly larger among deep default loans, at 13.5 percentage points. Households in deeper states of mortgage arrears also appear to have accumulated higher non-mortgage debts: the ratio of non-mortgage debt to income is 3.98 among those in deep default, and below 2.5 for the other two groups, while the share of non-mortgage debts in total debts is 26.8% for those in deep default, and below 20% for the lower-arrears groups. Comparing our measure of Adjusted *CLTV* with the traditionally-used *CLTV*, it is clear that the unconditional relationship between the depth of default and housing equity is much less apparent when adjusting for the mechanical bias in the construction of *CLTV*.

4. Empirical results

In this section, we present results from a three-category multinomial model using the SFS data. From Section 3, we define a reference category, “early distress”, which encompasses all households filling out an SFS with either zero or between 1 and 90 *DPD*. The probability of a loan being in default and deep default relative to being in early distress is estimated. The coefficients, presented in Table 6, cannot be directly compared to those of binary default models common to the literature, given that truly performing loans are not available in our data sample. Rather, we must interpret the results of the model of Table 6 as representing the effect of the $TinA_i$, $\mathbf{X_i}$ and $\mathbf{Z_i}$ on *PD* and *PDD*, conditional on having experienced some mortgage repayment difficulty. In the estimation sample, the *PD* is 18.76%, with *PDD* being 16.45%. All marginal effect estimates must be interpreted with these baseline probabilities in mind. The results of four models are presented in Table 6. The difference between the specifications is (i) in whether our Adjusted *CLTV* measure is included, or whether *CLTV* is included to increase comparability to previous literature (ii) in the way in which non-mortgage debts are captured in the data.

The first striking pattern in the model’s results is that most of the variables included in the model do not explain entry into early-stage default. The vast majority of the statistically significant impacts observed in the model are found in the deep default equations. We have initial evidence from these patterns that where household affordability shocks and other factors drive borrowers

Table 7
Income shock variable included. Multinomial Logit Results. Average Marginal Effects Reported.

	(Model 1)		(Model 2)		(Model 3)		(Model 4)	
	(1) 90–360	(2) 360+	(3) 90–360	(4) 360+	(5) 90–360	(6) 360+	(7) 90–360	(8) 360+
Time in Arrears	0.00341***	0.0162***	0.00354***	0.0158***	0.00341***	0.0158***	0.00353***	0.0154***
	(0.000163)	(0.000194)	(0.000165)	(0.000195)	(0.000170)	(0.000202)	(0.000172)	(0.000202)
FTB	0.0112	−0.0179***	0.0121*	−0.0153***	0.0116*	−0.0187***	0.0125*	−0.0160***
	(0.00705)	(0.00490)	(0.00707)	(0.00490)	(0.00705)	(0.00489)	(0.00706)	(0.00489)
Term	0.000129***	−0.000107***	0.000119**	−0.0000647*	0.000126***	−0.0000938***	0.000116**	−0.0000518
	(0.0000497)	(0.0000370)	(0.0000499)	(0.0000371)	(0.0000485)	(0.0000356)	(0.0000487)	(0.0000357)
SVR	0.0336**	0.0432***	0.0348**	0.0404***	0.0334**	0.0433***	0.0345**	0.0406***
	(0.0154)	(0.0123)	(0.0154)	(0.0122)	(0.0154)	(0.0123)	(0.0154)	(0.0122)
Tracker	0.0918***	0.130***	0.0933***	0.128***	0.0915***	0.130***	0.0930***	0.128***
	(0.0228)	(0.0163)	(0.0229)	(0.0164)	(0.0228)	(0.0163)	(0.0229)	(0.0164)
Curr Int Rate	0.0197***	0.0368***	0.0201***	0.0367***	0.0199***	0.0360***	0.0203***	0.0359***
	(0.00505)	(0.00391)	(0.00503)	(0.00389)	(0.00505)	(0.00392)	(0.00503)	(0.00390)
Adjusted CLTV	0.0000371	0.000686***	0.0000454	0.000685***				
	(0.0000938)	(0.0000693)	(0.0000934)	(0.0000687)				
CLTV					0.0000446	0.000651***	0.0000536	0.000649***
					(0.0000851)	(0.0000599)	(0.0000849)	(0.0000594)
Other Debt to Income	−0.000286	0.00222***			−0.000275	0.00220***		
	(0.000405)	(0.000263)			(0.000404)	(0.000262)		
Other Debt Share			−0.00257	0.109***			−0.00219	0.108***
			(0.0118)	(0.00826)			(0.0118)	(0.00826)
Monthly Net Income	−0.00196	−0.00176	−0.00252	−0.00488***	−0.00180	−0.00216	−0.00238	−0.00526***
	(0.00224)	(0.00171)	(0.00233)	(0.00176)	(0.00224)	(0.00172)	(0.00234)	(0.00176)
Divorced	0.0121	0.0169**	0.0114	0.0199***	0.0122	0.0165**	0.0115	0.0195***
	(0.0102)	(0.00716)	(0.0102)	(0.00714)	(0.0102)	(0.00714)	(0.0102)	(0.00713)
Unemployment Shock	−0.00582	0.0285***	−0.00551	0.0292***	−0.00591	0.0287***	−0.00560	0.0294***
	(0.00621)	(0.00451)	(0.00622)	(0.00449)	(0.00621)	(0.00450)	(0.00621)	(0.00449)
Δ Debt Service Ratio	0.00339	0.0637***	0.000266	0.0387*	0.00155	0.0702***	−0.00154	0.0450**
	(0.0322)	(0.0229)	(0.0323)	(0.0228)	(0.0322)	(0.0230)	(0.0323)	(0.0228)
Debt Service Ratio	0.0181	−0.0112	0.0188	0.0190	0.0209	−0.0199	0.0215	0.0103
	(0.0322)	(0.0229)	(0.0323)	(0.0227)	(0.0322)	(0.0230)	(0.0324)	(0.0228)
Single, 1/2	0.00979	0.0122	0.0101	0.0122*	0.00977	0.0121	0.0101	0.0122*
	(0.0103)	(0.00744)	(0.0103)	(0.00738)	(0.0103)	(0.00742)	(0.0103)	(0.00736)
Single, 3+	0.0173	0.0237*	0.0185	0.0239**	0.0176	0.0235*	0.0188	0.0237*
	(0.0194)	(0.0122)	(0.0195)	(0.0121)	(0.0194)	(0.0122)	(0.0195)	(0.0121)
Couple, Zero	0.0164*	0.00852	0.0176*	0.00859	0.0163*	0.00840	0.0176*	0.00844
	(0.00933)	(0.00679)	(0.00934)	(0.00672)	(0.00932)	(0.00678)	(0.00934)	(0.00671)
Couple, 1/2	0.00456	−0.00374	0.00535	−0.00252	0.00453	−0.00374	0.00536	−0.00254
	(0.00834)	(0.00610)	(0.00835)	(0.00604)	(0.00834)	(0.00609)	(0.00835)	(0.00604)
Couple, 3+	0.00926	0.00392	0.0105	0.00489	0.00917	0.00408	0.0104	0.00502
	(0.00945)	(0.00677)	(0.00947)	(0.00670)	(0.00944)	(0.00676)	(0.00946)	(0.00670)
Observations	19,941	19,941	19,941	19,941	19,941	19,941	19,941	19,941

Controls for county, loan age (quadratic), borrower age (quadratic) and bank included in all models Robust standard errors in parentheses;
* $p < .1$.
** $p < .05$.
*** $p < .01$.

into default, they have severe impacts that lead to the continued accumulation of large quantities of arrears.

The coefficients on *TinA* are extremely stable across the four models, with one month in arrears is associated with roughly a 0.3 percentage point increase in *PD*, and a 1.6 percentage point increase in *PDD*. These results intuitively suggest that our innovation in controlling explicitly for the duration since the onset of a negative shock has important explanatory power in all models. FTB mortgages are shown to be less likely to enter deep default, with the differential being between 1 and 2 percentage points in all models. Mortgages originated with a longer term exhibit a mixed pattern whereby they appear to be associated with higher *PD* but with either lower or statistically insignificant *PDD*.

Standard Variable Rate and tracker mortgages are shown to have significantly higher probabilities of deeper states of arrears than fixed rate loans. The coefficients suggest that the impact of a tracker mortgage on *PDD* is to increase the probability by 12–13 percentage points relative to fixed rate loans, while the analogous effect of SVRs is smaller at 4–4.3%. Beyond the impact of rate types, which may capture some underlying borrower heterogeneity in risk preferences, the interest rate on the loan has a positive association with credit risk, with a 100 bps rate increase associated with 1.8 to 1.9 percentage point increase in *PD* and a 3.5–3.6 percentage point increase in *PDD*.

Housing equity is shown to have a positive impact on *PDD* and no impact on *PD*. A ten percentage point increase in either *CLTV* or the adjusted measure is estimated to lead to a 0.6% increase in *PDD*.

Mortgage repayment capacity, as measured by the ratio of monthly repayment to monthly household income (Debt Service Ratio, DSR), is an important driver of both *PD* and *PDD*. A ten per cent increase in the DSR is associated with an increase of 0.23–0.27 and 0.3–0.4 percentage points in *PD* and *PDD*, respectively. In addition, household-level unemployment is shown to have an important effect on *PDD*. Across all models, a robust effect of close to 3 percentage points is found. Non-mortgage debts are associated with deeper states of arrears: a ten per cent increase in the ratio of non-mortgage debt to total debts leads to a 1.1% increase in *PDD*. An increase of one in the ratio of non-mortgage debt to annual income leads to a .2% increase in *PDD*.

Table 8
DSR and Δ DSR as the only proxies of mortgage affordability included in model. Multinomial Logit Results. Average Marginal Effects Reported.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Time in Arrears	0.00362***	0.0159***	0.00371***	0.0157***	0.00362***	0.0156***	0.00370***	0.0153***
	(0.000159)	(0.000189)	(0.000161)	(0.000190)	(0.000165)	(0.000195)	(0.000166)	(0.000196)
FTB	0.0105	−0.0180***	0.0113	−0.0149***	0.0109	−0.0187***	0.0117*	−0.0157***
	(0.00701)	(0.00490)	(0.00705)	(0.00492)	(0.00700)	(0.00489)	(0.00704)	(0.00491)
Term	0.000160***	−0.0000654*	0.000148***	−0.0000253	0.000155***	−0.0000545	0.000143***	−0.0000154
	(0.0000495)	(0.0000384)	(0.0000497)	(0.0000385)	(0.0000484)	(0.0000369)	(0.0000486)	(0.0000370)
SVR	0.0258*	0.0125	0.0267*	0.0104	0.0252*	0.0134	0.0262*	0.0112
	(0.0145)	(0.0112)	(0.0145)	(0.0110)	(0.0145)	(0.0112)	(0.0145)	(0.0111)
Tracker	0.0250*	0.00801	0.0255*	0.00615	0.0238*	0.0107	0.0244*	0.00875
	(0.0144)	(0.0112)	(0.0144)	(0.0110)	(0.0144)	(0.0112)	(0.0144)	(0.0111)
Adjusted CLTV	0.0000224	0.000674***	0.0000267	0.000648***				
	(0.0000919)	(0.0000693)	(0.0000917)	(0.0000688)				
CLTV					0.0000367	0.000643***	0.0000408	0.000619***
					(0.0000831)	(0.0000593)	(0.0000831)	(0.0000590)
Divorced	0.00897	0.0153**	0.00826	0.0187***	0.00906	0.0151**	0.00837	0.0185***
	(0.0101)	(0.00703)	(0.0101)	(0.00705)	(0.0101)	(0.00702)	(0.0101)	(0.00704)
Δ DSR	−0.000240	0.0622***	−0.0000590	0.0459**	−0.00223	0.0709***	−0.00195	0.0543**
	(0.0319)	(0.0230)	(0.0320)	(0.0227)	(0.0320)	(0.0230)	(0.0320)	(0.0228)
DSR	0.0252	0.0116	0.0230	0.0387*	0.0277	0.00154	0.0254	0.0288
	(0.0321)	(0.0230)	(0.0323)	(0.0228)	(0.0322)	(0.0231)	(0.0324)	(0.0229)
Other Debt to Income	−0.000538	0.00197***			−0.000526	0.00194***		
	(0.000404)	(0.000253)			(0.000404)	(0.000252)		
Other Debt Share			−0.0118	0.0936***			−0.0113	0.0926***
			(0.0112)	(0.00783)			(0.0112)	(0.00783)
Single, 1/2	0.00692	0.00802	0.00722	0.00744	0.00703	0.00789	0.00734	0.00730
	(0.0102)	(0.00738)	(0.0102)	(0.00733)	(0.0102)	(0.00737)	(0.0102)	(0.00732)
Single, 3+	0.00941	0.0232*	0.0103	0.0216*	0.00980	0.0228*	0.0107	0.0212*
	(0.0189)	(0.0119)	(0.0189)	(0.0119)	(0.0189)	(0.0119)	(0.0190)	(0.0119)
Couple, Zero	0.0197**	0.0101	0.0205**	0.00830	0.0197**	0.00956	0.0205**	0.00781
	(0.00924)	(0.00702)	(0.00924)	(0.00695)	(0.00924)	(0.00701)	(0.00924)	(0.00693)
Couple, 1/2	0.000546	−0.0123**	0.000687	−0.0137**	0.000657	−0.0127**	0.000799	−0.0141**
	(0.00807)	(0.00597)	(0.00807)	(0.00591)	(0.00807)	(0.00596)	(0.00807)	(0.00590)
Couple, 3+	0.00339	−0.00530	0.00363	−0.00757	0.00349	−0.00557	0.00373	−0.00783
	(0.00897)	(0.00651)	(0.00896)	(0.00642)	(0.00897)	(0.00650)	(0.00896)	(0.00641)
Observations	19,941	19,941	19,941	19,941	19,941	19,941	19,941	19,941

Marginal effects; Standard errors in parentheses.Relative to the baseline model, Interest Rate, Monthly Net Income and Unemployment Shock have been excluded.
* $p < .1$.
** $p < .05$.
*** $p < .01$.

Monthly after-tax household income is found to impact the probability of deep default: a fall of € 1000 per month is associated with a 0.3–0.6 percentage point increase in *PDD*.

The bottom panel of Table 6 reports results for household composition. Relative to single borrowers without children, single people with three or more children, who represent just two per cent of the sample, have 2 percentage points higher *PDD*. In the majority of cases, family composition does not impact the depth of default. However, households experiencing a divorce since mortgage origination are significantly higher risk, with such a shock associated with *PDD* increases of 2 percentage points.

In Table 7, we extend the analysis by replicating the model of Table 6 to incorporate the role of Δ DSR, our measure of the *shock* to mortgage affordability since origination. These estimates provide novel insights by showing that the level of mortgage affordability itself does not have a statistically significant impact on the depth of mortgage default once the affordability shock is controlled for. A ten percentage point increase in the DSR since origination leads to a 0.4 to 0.7% increase in *PDD*, depending on the model specification. The estimated impact of close to all significant explanatory variables are stable between Tables 6 and 7, indicating that factors apart from our direct measure of mortgage affordability are not impacted by the inclusion of Δ DSR in the model.

We can think about the relative economic magnitudes of our estimated effects by observing the impact of a one-standard-deviation increase in our continuous variables on *PDD*. The impact for the ratio of non-mortgage debts to income is 1.4%, while for the ratio of non-mortgage debts to total debt, the impact is 2.6%. The equivalent effect for the DSR in Table 6 is 1.9%, while the impact of Δ DSR in Table 7 is 1.6%. Both *CLTV* and our adjusted measure of housing equity have a one-SD impact of 2.8–2.9 percentage points on *PDD*, meaning that they are relatively large in magnitude, and as important as an unemployment shock in driving long-term mortgage arrears.

We test the robustness of the affordability measures in our model by including the DSR and Δ DSR measures while excluding other proxies for mortgage affordability, namely the interest rate, unemployment shock and net monthly income. Table 8 reports that, across the four models, the Δ DSR coefficient in the deep default equation remains extremely stable when compared to that in columns (2), (4), (6) and (8) of Table 6. These findings suggest that (i) the affordability shock estimates of Table 6 are reliable (ii) the significance of the interest rate, unemployment shock and net monthly income point to the importance of the source of change in Δ DSR and not just the overall size of the change.

Given that the inclusion of an explicit measure of the duration since the onset of a shock is not common in the literature on mortgage defaults, we re-run all the specifications of Table 6 without *TinA*. The results of these specifications, reported in Table A.2 should therefore be more comparable to the extant cross-sectional binary default literature. Average marginal effect estimates on income, non-mortgage debts, divorce, unemployment, DSR are all larger, sometimes by orders of magnitude, in this specification than in Table 6. Many effects, particularly in the *PD* equation, become statistically significant once *TinA* is omitted. Further, many of the dummy variables for household composition appear to impact default in these models, suggesting that early onset of shocks was more prevalent in Ireland for more vulnerable family types. On housing equity, we find that *CLTV* is now estimated to significantly impact *PD*, and to have an MFX of .002 in the *PDD* equation, relative to an effect of .0007 in Table 6. This suggests intuitively that *TinA* and housing equity are closely related, with the omission of *TinA* from our specification leading to an erroneous tripling in the point estimate on *CLTV*. The results of Table A.2 suggest that there is important correlation between *TinA* and our main explanatory variables, implying that a model that omits *TinA* is likely to overestimate the importance of $\mathbf{X_i}$ and $\mathbf{Z_i}$.

5. Conclusion

A vast existing literature has treated all mortgages as homogeneous by virtue of the use of binary models of mortgage default. The issue of homogeneity among defaulted borrowers is of new importance given the response of many developed economies to avoid the repossession model in favor of loan modification and restructuring. Using a unique dataset on Irish mortgage borrowers, we extend the current literature by treating mortgages in deep states of arrears (greater than one year past due) differentially to those in earlier stages of default. Such a distinction is crucial given that previous work has shown that mortgages in deeper default are less likely to ever begin repayment (“cure”). These lower cure probabilities lead to higher estimates of Loss Given Default and expected losses for mortgage lenders.

The dataset available allows us to estimate the effect of an extremely rich set of explanatory factors including interest rates, housing equity, unemployment, income, non-mortgage debt volumes, household composition and divorce. Our estimates suggest that these factors explain mortgage default in a direction consistent with previous literature. In all cases, the impact on the probability of deep default is found to be larger than that on entering earlier stages of default. These findings suggest that shocks to the ability to repay are extremely important, and when they occur, they have severe impacts which lead to rapid accumulation of large arrears balances. Further, we present evidence that the “double trigger” impact is in operation when considering entry to deep mortgage arrears: housing equity is found to have a similar economic impact to an unemployment shock, and (in standard deviation terms) a larger impact than the level of non-mortgage debts or the shock to mortgage affordability. As well as identifying patterns that can help in the early identification of impending growth in arrears, these findings are key to the design and efficiency of mortgage modification schemes which can involve a large amount of public spending.

Appendix A

Table A.1
Definitions of default in micro-level studies of mortgage default.

Study	Country	Dataset	Definition
Gyourko and Tracy (2014)	USA	Lender Processing Services Inc. Applied Analytics	90 DPD
McCarthy (2014)	Ireland	Central Bank of Ireland Loan Level Data	90 DPD
Gerardi et al. (2013)	USA	PSID Supplement on Housing, Mortgage Distress and Wealth Data	60 DPD
Lydon and McCarthy (2013)	Ireland	Central Bank of Ireland Loan Level Data	90 DPD
Kau et al. (2011)	USA	Black Box Logic LLC	Foreclosure
Kelly (2011)	Ireland	Central Bank of Ireland Loan Level Data	Three categories: 0 ; 0–90; 90+ DPD
Elul et al. (2010)	USA	Loan Performance and Lender Processing Services and Equifax data	60 DPD
Bhutta et al. (2010)	USA	LoanPerformance, First American CoreLogic	90 DPD for two consecutive months
Mayer et al. (2009)	USA	First American LoanPerformance	“Seriously Delinquent”, 90 DPD
Bajari et al. (2008)	USA	LoanPerformance	Foreclosure
Foote et al. (2008)	USA	Warren Group, Massacheusetts Registry of Deeds	Foreclosure
Boheim and Taylor (2000)	UK	British Household Panel Survey	Survey response on payment difficulty

Table A.2
Multinomial Logit Results. *TinA* not included in model of Table 6. Average Marginal Effects Reported.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FTB	0.0153**	−0.0134**	0.0174**	−0.00501	0.00622	−0.0345***	0.00894	−0.0255***
	(0.00772)	(0.00659)	(0.00776)	(0.00670)	(0.00753)	(0.00606)	(0.00759)	(0.00618)
Term	0.000315***	−0.0000325	0.000317***	0.0000449	0.000153***	−0.000428***	0.000153***	−0.000327***
	(0.0000521)	(0.0000473)	(0.0000521)	(0.0000468)	(0.0000523)	(0.0000484)	(0.0000525)	(0.0000477)
SVR	0.0827***	0.121***	0.0830***	0.115***	0.0793***	0.110***	0.0792***	0.104***
	(0.0158)	(0.0168)	(0.0158)	(0.0163)	(0.0157)	(0.0161)	(0.0157)	(0.0158)
Tracker	0.154***	0.197***	0.154***	0.195***	0.150***	0.161***	0.151***	0.161***
	(0.0233)	(0.0241)	(0.0231)	(0.0235)	(0.0236)	(0.0239)	(0.0235)	(0.0235)
Curr Int Rate	0.0405***	0.0378***	0.0407***	0.0395***	0.0367***	0.0296***	0.0371***	0.0316***
	(0.00542)	(0.00494)	(0.00541)	(0.00487)	(0.00544)	(0.00510)	(0.00543)	(0.00502)
Adjusted CLTV	−0.000325***	0.000480***	−0.000305***	0.000559***				
	(0.0000970)	(0.0000922)	(0.0000968)	(0.0000900)				
CLTV					0.000334***	0.00202***	0.000363***	0.00200***
					(0.0000889)	(0.0000849)	(0.0000884)	(0.0000821)
Other Debt to Income	0.000329	0.00410***			0.000285	0.00372***		
	(0.000463)	(0.000339)			(0.000458)	(0.000333)		
Other Debt Share			0.0378***	0.243***			0.0430***	0.237***
			(0.0120)	(0.00932)			(0.0119)	(0.00930)

(*continued on next page*)

Table A.2 (*continued*)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Monthly Net Income	0.00146	−0.0109***	0.000188	−0.0220***	−0.00149	−0.0190***	−0.00311	−0.0296***
	(0.00230)	(0.00226)	(0.00243)	(0.00243)	(0.00234)	(0.00232)	(0.00246)	(0.00247)
Divorced	0.0274**	0.0584***	0.0276**	0.0628***	0.0253**	0.0483***	0.0258**	0.0524***
	(0.0112)	(0.0107)	(0.0112)	(0.0106)	(0.0111)	(0.0101)	(0.0111)	(0.0101)
Unemployment Shock	0.00251	0.0414***	0.00253	0.0417***	0.00571	0.0455***	0.00583	0.0449***
	(0.00672)	(0.00640)	(0.00672)	(0.00635)	(0.00676)	(0.00633)	(0.00676)	(0.00626)
DSR	0.0540***	0.0992***	0.0530***	0.104***	0.0327***	0.0549***	0.0315***	0.0597***
	(0.0111)	(0.00888)	(0.0111)	(0.00868)	(0.0112)	(0.00852)	(0.0111)	(0.00831)
Single, 1/2	0.0136	0.0343***	0.0140	0.0336***	0.0147	0.0366***	0.0152	0.0353***
	(0.0113)	(0.0106)	(0.0113)	(0.0105)	(0.0113)	(0.0105)	(0.0114)	(0.0103)
Single, 3+	0.0351*	0.102***	0.0353*	0.106***	0.0366*	0.103***	0.0372*	0.106***
	(0.0209)	(0.0207)	(0.0209)	(0.0206)	(0.0210)	(0.0201)	(0.0210)	(0.0200)
Couple, Zero	0.0375***	0.00768	0.0382***	0.00971	0.0356***	0.00837	0.0365***	0.0103
	(0.0105)	(0.00896)	(0.0105)	(0.00888)	(0.0105)	(0.00881)	(0.0105)	(0.00871)
Couple, 1/2	0.0106	−0.00400	0.0117	−0.000127	0.0107	0.00126	0.0121	0.00484
	(0.00908)	(0.00807)	(0.00910)	(0.00799)	(0.00906)	(0.00797)	(0.00907)	(0.00789)
Couple, 3+	0.0264**	0.0181*	0.0274**	0.0235**	0.0295***	0.0301***	0.0306***	0.0352***
	(0.0106)	(0.00966)	(0.0106)	(0.00963)	(0.0106)	(0.00970)	(0.0107)	(0.00964)
Observations	21,086	21,086	21,086	21,086	21,086	21,086	21,086	21,086
Pseudo R^2								

Controls for county, loan age (quadratic), borrower age (quadratic) and bank included in all models.Robust standard errors in parentheses;

* $p < .1$.

** $p < .05$.

*** $p < .01$.

References

Bajari, P., Chu, C.S., Park, M., 2008. An Empirical Model of Subprime Mortgage Default From 2000 to 2007. NBER Working Papers 14625. National Bureau of Economic Research, Inc.

Been, V., Weselcouch, M., Voicu, I., Murff, S., 2013. Determinants of the incidence of U.S. mortgage loan modifications. Journalof Banking & Finance 37, 3951–3973.

Bhutta, N., Dokko, J., Shan, H., 2010. The Depth of Negative Equity and Mortgage Default Decisions. Finance and Economics Discussion Series, Board of Governors of the Federal Reserve System (U.S.) 2010-35. Board of Governors of the Federal Reserve System (U.S.).

Boheim, R., Taylor, M.P., 2000. My home was my castle: evictions and repossessions in Britain. Journal of Housing Economics 9 (4), 287–319.

Campbell, J.Y., Giglio, S., Pathak, P., 2011. Forced sales and house prices. American Economic Review 101 (5), 2108–2131.

Elul, R., Souleles, N.S., Chomsisengphet, S., Glennon, D., Hunt, R., 2010. What "Triggers" mortgage default? American Economic Review, American Economic Association 100 (2), 490–494.

Foote, C.L., Gerardi, K., Willen, P.S., 2008. Negative equity and foreclosure: theory and evidence. Journal of Urban Economics 64 (2), 234–245.

Gerardi, K., Herkenhoff, K.F., Ohanian, L.E., Willen, P.S., 2013. Unemployment, Negative Equity, and Strategic Default. Working Paper, Federal Reserve Bank of Atlanta 2013-04. Federal Reserve Bank of Atlanta.

Gerardi, K., Rosenblatt, E., Willen, P.S., Yao, V., 2012. Foreclosure externalities: Some new evidence. NBER Working Papers 18353. National Bureau of Economic Research, Inc.

Guiso, L., Sapienza, P., Zingales, L., 2013. The determinants of attitudes toward strategic default on mortgages. Journal of Finance 68 (4), 1473–1515.

Gyourko, J., Tracy, J., 2014. Reconciling theory and empirics on the role of unemployment in mortgage default. Journal of Urban Economics 80 (C), 87–96.

Jorda, O., Schularick, M., Taylor, A., 2014. The great mortgaging: housing finance, crises and business cycles. NBER Working Papers 20501. National Bureau of Economic Research, Inc.

Kau, J.B., Keenan, D.C., Lyubimov, C., Carlos Slawson, V., 2011. Subprime mortgage default. Journal of Urban Economics 70 (2–3), 75–87.

Kelly, R., 2011. The Good, The Bad and The Impaired - A Credit Risk Model of the Irish Mortgage Market. Research Technical Papers 13/RT/11. Central Bank of Ireland.

Kelly, R., McCann, F., 2015. Mortgage defaults and the loan to value ratio. mimeo forthcoming. Central Bank of Ireland.

Kelly, R., O'Malley, T., O'Toole, C., 2014. Do first time buyers default less? Implications for macro-prudential policy. Economic Letters 14/EL/14. Central Bank of Ireland.

Kelly, R., OMalley, T., 2016. The good, the bad and the impaired: a credit risk model of the Irish mortgage market. Journal of Financial Stability 22 (C), 1–9.

Kennedy, G., McIndoe-Calder, T., 2012. The irish mortgage market: stylised facts, negative equity and arrears. Quarterly Bulletin Articles, Central Bank of Ireland 85–108.

Lydon, R., McCarthy, Y., 2013. What lies beneath? understanding recent trends in irish mortgage arrears. The Economic and Social Review, Economic and Social Studies 44 (1), 117–150.

Mayer, C., Morrison, E., Piskorski, T., Gupta, A., 2014. Mortgage modification and strategic behavior: evidence from a legal settlement with countrywide. American Economic Review 104 (9), 2830–2857.

Mayer, C., Pence, K., Sherlund, S.M., 2009. The rise in mortgage defaults. Journal of Economic Perspectives 23 (1), 27–50. doi:10.1257/jep.23.1.27.

McCann, F., 2014. Modelling default transitions in the UK mortgage market. Research Technical Papers 18/RT/14. Central Bank of Ireland.

McCarthy, Y., 2014. Dis-entangling the mortgage arrears crisis: The role of the labour market, income volatility and housing equity. Research Technical Papers 02/RT/14. Central Bank of Ireland.

Mian, A., Sufi, A., Trebbi, F., 2011. Foreclosures, House Prices, and the Real Economy. IMES Discussion Paper Series 11-E-27. Institute for Monetary and Economic Studies, Bank of Japan.

Qi, M., Xiaolong, Y., 2009. Loss given default of high loan to value residential mortgages. Journal of Banking & Finance 33, 778–799.