Irish Mortgage Default Optionality*

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Abstract

The owner of a residential property subject to a nonrecourse mortgage essentially has a put option against the market value of the property. If the market price of the property falls sufficiently, the owner can surrender the property to the mortgage issuer and in exchange receive full offset of the cash flow liability of the mortgage loan. A similar but diluted put optionality holds for recourse mortgages if there are legal or practical limits to the mortgage issuer's recourse claim against the owner's future income. Previous research based on American data finds that put optionality is an important, but not exclusive, determinant of mortgage default. This paper utilizes a database of troubled Irish mortgages to analyze the influence of put optionality on Irish property owners' default behaviour. We find that put optionality is a very important explanatory variable for observed Irish mortgage defaults, complementing and strengthening existing empirical findings from US mortgage markets.

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1 Introduction

The owner of a residential property subject to a nonrecourse mortgage who is willing to renege on his loan essentially holds a put option against the market value of the property. If the market price of the property falls sufficiently, the owner can surrender the property to the mortgage lender and in exchange receive full offset of his cash flow liability from the mortgage loan. In options terminology, the homeowner has a long-term American put option on a dividend-paying asset (the implicit rental yield of the property serves as the dividend flow) with exercise price equal to the cash-equivalent value of the mortgage liability. The moneyness of the put option is one minus the reciprocal of the loan-to-value ratio of the mortgage. A similar, but diluted, put optionality holds for recourse mortgages, since there are legal and practical limits to a mortgage lender's recourse claim against the owner's future income, for example, relief from this claim through personal bankruptcy. In most situations, both the homeowner and mortgage lender incur substantial transactions costs upon exercise by the homeowner of this put option. This two-sided transactions-cost feature of the put option leads to a bargaining game between the homeowner and mortgage lender, with the homeowner potentially able in some circumstances to gain mortgage payment concessions by threatening to surrender the asset but not doing so. The bargaining power of the mortgage borrower in default seeking repayment concessions increases with the moneyness of the put option.

Particularly in the case of a recourse mortgage, there are reputational costs and social/ethical considerations for the homeowner from defaulting, since in doing so the homeowner has violated the terms of an agreed contract for personal gain. In many cases, the mortgage lender will continue to receive (more valuable) required mortgage payments even when options theory predicts that it will be forced to accept surrender of the property.

Most existing Irish residential mortgages are contractually written to be full recourse and with unhindered security against the property. However, in recent years a number of legislative and regulatory changes have altered the *de facto* nature of mortgage claims. Irish residential mortgages are now, in practice, limited-recourse contracts and have strictly limited security against the property asset, and high transactions costs for the mortgage lender in exercising the security claim. Given the extremely large falls in Irish residential property values during the period 2008 to 2012, it is sensible to examine whether put optionality helps to explain the explosive increase in

Irish mortgage arrears over roughly that same period.

This paper empirically examines the influence of put optionality on the default behaviour of Irish mortgage borrowers. We rely on a large database of Irish mortgages provided to us by a mortgage lender in Ireland, Permanent TSB. The database covers all mortgages at Permanent TSB for which the holder has submitted a Standard Financial Statement (SFS), giving a sample of 28,377 mortgage accounts. Submitting an SFS is a required component of the Central Bank of Ireland's mandated mortgage arrears resolution process (MARP). The entry of a mortgage borrower into MARP is either at the initiation of the bank after one or more missed mortgage payments or, less commonly, by the mortgage borrower looking to engage with the bank for help with their mortgage payment difficulties. The sample is doubly-censored since it consists only of mortgages which have been brought into MARP, and does not include troubled mortgages which should be in MARP but where the mortgage borrower has refused to submit the required SFS. Our data panel consists of information from the SFS collated with information from the original loan application and some other loan-specific data items. Roughly half the mortgages in our sample are in default, defined as greater than 90 days worth of accumulated payment arrears, and half are not in default.

Our main empirical task is to build a model explaining which of this observed subset of all mortages, that is the subset of mortgages in MARP where the mortgage borrower has submitted an SFS, are in default, and which are not in default. We use a combination of analysis of variance, multivariable probit models and nonparametric and semiparametric kernel-based estimators. We find that put optionality is a significant explanatory variable for Irish mortgage default. The loan-to-value ratio, which measures the moneyness of the implicit put option, is the most powerful variable in generating differences in average default rates across portfolios of loans double-sorted by levels of explanatory variables. In a multivariate probit model of mortgage default, loan-to-value is again the most important explanatory variable, measured by marginal contribution to the probability of default. The put-optionality effect is particulary strong when combined with household income stress, supporting the "dual trigger" model of mortgage default. Whereas in US data, affordability is generally found to be more important than put-optionality as a predictor of default, within our (doubly-censored) Irish sample, put-optionality appears more important than affordability as a predictor of default.

Using nonparametric and semiparametric methods, we find some evidence for an options-type convexity in the functional link of loan-to-value to mortgage default probability. This convex relationship also conforms to findings in US-based research on the effect of loan-to-value on mortgage default rates.

Section two reviews the existing literature and critically examines the insights which options theory can provide regarding mortgage default behaviour in Ireland. Section three describes our econometric model of mortgage default. Section four empirically examines the default behaviour of mortgages in our database. Section five summarizes the paper.

2 Optionality and Mortgage Contracts

There is a large research literature examining the impact of the implicit put option in mortgage contracts on default behaviour by mortgage borrowers. The empirical component of this research is mostly based on US mortgage market data. We will briefly review a few of the papers with particular relevance.

The original insight for modeling mortgage default as a put option is credited to Asay (1978). Deng et al. (2000) show empirically that a continuous-time, frictionless market, Black-Scholes-type theory of mortgage default as put option exercise provides useful empirical content, but is not sufficient as an empirical model. Unlike the exercise of a securities-market traded put option on a stock, defaulting on a mortgage has large fixed costs, and a potentially large impact on the future economic opportunities of the mortgage borrower, particularly through its impact on their personal credit rating and the availability of new mortgage finance to them. Deng et al. also note that mortgage default is not fully "rational" in the sense of cash-flow maximizing – there are moral/social/psychological aspects to the default decision. Most of the recent literature does not rely on the continuous-time, frictionless market assumptions of Black-Scholes type models.

Elmer and Seelig (1998) build a model of mortgage default which combines both inability-to-pay and put-optionality as causes of default. Using US data aggregated at the state and regional level, they find that both causes play a role in mortgage default, but that inability-to-pay is relatively stronger. The data used in the paper pre-dates the volatile US property price declines of the post-2007 period.

Using loan-level data, Tirupattur et al. (2010) conclude that defaults driven by negative equity, rather than ability to pay, are a significant phenomenon in US residential mortgages over their sample period. A borrower is defined as strategically in default (that is, exercising their put option) when their mortgage goes from current to 30-, 60- and then 90-days in arrears without any payment during this period or any subsequent payments, while the borrower continues to service non-mortgage loans. Strategic defaults increase over time in concert with the decline in US residential property prices and by the end of the sample (February 2010), they represent 12% of all defaulted mortgages. Wyman (2009) uses a similar approach and estimates that by second quarter of 2009, 19% of all defaults were strategic.

Bhutta et al. (2010) build a theoretical model of mortgage borrower default decisions combining inability-to-pay and put-optionality reasons for default. They test the model using a loan-level database, combined with micro-regional property price indices, covering several US states with large property price declines (and business cycle recessions) in the post-2007 period. They find that, considered separately, inability to pay is the more important source of default decisions, but that put optionality also plays a prominent role. They find that when negative equity exceeds 50 percent of the property's value, half of the defaulters are exercising their put option rather than experiencing any inability to pay. Also, Bhutta et al. argue that their empirical findings support Foote's (2008) "dual-trigger" model of default – default is highest when householders experience *both* simultaneous income falls *and* negative equity increases. The two causes of default interact and reinforce each other.

Bhutta et al. note that a contributory factor in strategic default is the long "free-rent" period between original default and repossession; this period lasts at least eight to twelve months in most US states, dependent upon the specific legal statutes of the state. The implicit cash value of the free-rent period adds to the put-optionality payoff from default and further incentivizes strategic default. Cutts and Merrill (2008) look in detail at cross-state differences in the length of the free-rent period associated with necessary legal delays in the repossession process. They find that states with relatively shorter periods have generally better outcomes in terms of cure-rates (the proportion of households with mortgages in arrears that get back on track and keep their property). They estimate an "optimal" repossession interval of 270 days from original missed payment to physical repossession, consisting of 150 days of customer counseling/assistance with mortgage arrears, a default declaration notice by the lender, and then 120 days before physical repossession.

Relying on survey data, Guiso et al. (2011) find that social considerations, such as morality and fairness, influence borrowers on the acceptability of strategically defaulting. They estimate that in their sample 26% of existing defaults are strategic. They find that almost no households will deliberately choose to default (given ability to pay) if negative equity shortfall is less than 10% of the value of the house; 17% of households will choose to default even if they can afford to pay their mortgage when negative equity reaches 50% of the value of the property. Burke and Mihaly (2012), also based on survey data, find that social perceptions about the acceptability of strategic default, and financial literacy (the ability to navigate the US bankruptcy system) influence household's tendency toward strategic default. Seiler et al. (2012) report that networks are an important determinant of strategic default: borrowers who have family and friends in default are more likely to strategically default themselves. Towe and Lawley (2010) also find that social interactions play a significant role in the decision to default, in that having a neighbour in foreclosure increases the probability of default by 28%.

Elul et al. (2010) use an econometric framework somewhat similar to our own. They define default as accumulated arrears of 60 days or more, and estimate a logit model of binary default outcomes based on individual-credit-record data, together with nationwide quarterly interest rate data and quarterly US state-level unemployment rate changes. They find that both negative equity, which they interpret as put-optionality, and inability to pay have a significant effect on mortgage default probability. They also find that the two causes interact, so that mortgage default rates are particularly high when negative equity is combined with stressed ability to pay. Elul et al. also explore the possibility of a nonlinear impact of negative equity on mortgage default rates and find some confirmatory evidence.

Trautmann and Vlahu (2011) build a game-theoretic model of *borrower runs*: the tendency of borrowers to deliberately choose default when they perceive balance sheet weakness at the lending bank. Borrowers know that weak banks are likely to be less aggressive in quickly repossessing property, and also that the long-term relationship of the borrower with the bank has less value if the bank is weak. Since borrower loan nonpayments aggravate the weakness of the bank's balance sheet, borrower runs can self-reinforce in the same way as bank depositor runs.

The bargaining-game perspective of Trautmann and Vlahu highlights an important bargaining-game benefit to strategic default which increases as the moneyness of the implicit put option increases. Mortgage borrowers are aware that the lending bank must pay a large transactions cost in repossessing a property, and that the bank would benefit if it could negotiate reduced-value payment terms rather than repossess a negative-equity property. If the bank does not have full recourse to all the borrower's future income, then negative equity in the loan creates a gap between the present value of full mortgage payments and the present value of the minimum mortgage payments that the bank will hypothetically accept to avoid costly repossession. Strategic default (particularly in Ireland where repossession is very costly and difficult for banks) can be employed as a credible threat in negotiations for improved payment terms. Given the structure of Irish mortgage contracts (limited recourse, very costly repossession, banks with weak balance sheets) this is likely to be an important consideration in the Irish case.

Lydon and McCarthy (2011) provide an analysis of Irish mortgage market default based on data collected from four Irish banks during the Central Bank of Ireland's 2010 stress-testing review of the domestic banking sector. Like Elul et al. (2010) and this paper they use a static probit model of mortgage default based on individual loan characteristics. They argue that their static probit model results support a 'dual-trigger' model of default in which both affordability and put-optionality (that is, high loan-to-value ratios) impact household mortgage default. They also find that the regional unemployment rate, as a proxy for local economic shocks, has an impact on regional average default rates. Using a dynamic model applied to regional loan portfolios rather than individual loans, they can not confidently identify a put-optionality effect on default for regional home loan portfolios, but the effect is statistically significant for regional buy-to-let loan portfolios.

One obvious concern is the applicability of US-based research for modeling the default behaviour of Irish mortgage borrowers. There are important social, cultural, regulatory, and legal differences between U.S. and Irish residental mortgage markets. The Irish legal and regulatory environment has not been constant over the our sample period. Starting with the 2009 Land Reform Act, which contained a legal flaw rendering residential property repossession virtually impossible in Ireland, there have been a variety of changes to repossession, bankruptcy, and personal insolvency laws and regulation. The legal flaw in the 2009 Land Reform Act was eventually removed after sustained pressure from Ireland's international lenders under the sovereign bail-out programme (the International Monetary Fund, European Central Bank and European Union). From an international perspective, the current Irish system is borrower-friendly and repossession is slow and costly;

see Mac Coille et al. (2013) for a review. Coincidentally or otherwise, during the economically-turbulent period in which these regulatory and legal changes to mortgage contract enforcement were implemented, Irish mortgage arrears grew explosively. Figure 1 compares the time-series patterns of Irish mortgage defaults, the unemployment rate, per capital real income, and residential property prices over the period Q4 2002 - Q2 2013; all the series are normalized to 100 at the starting date of mortgage default data availability, Q3 2009.

3 Linear, Nonparametric, and Partially Linear Index Probit Models of Mortgage Default in a Panel Dataset

3.1 Linear Index Probit: A Brief Review

Our basic econometric model is a linear-index probit model of default. We assume that for each mortgage, the mortgage borrower's default outcome is based on an unobserved (by the econometrician) decision index v_i; if $v_i > 0$ then the mortage holder defaults. Each mortgage borrower's decision index is a linear combination of a $k-$vector of explanatory variables x_i with linear coefficients β plus an unobservable individual-specific random component ε_i capturing default-relevant idiosyncratic effects:

$$v_i = \beta_0 + \beta' x_i + \varepsilon_i \tag{1}$$

and we assume that ε_i has a standard normal distribution and is independent across mortgage borrowers. Let d_i denote the observable binary variable which is 1 if the mortgage borrower has defaulted and 0 otherwise. Let $\Phi(\cdot)$ denote the cumulative probability function of a standard normal variate. Given observation of $\{d_i, x_i\}_{i=1,\dots,n}$ maximum likelihood estimation of (β_0, β) is straightforward:

$$\begin{aligned}(\beta_0, \beta) = \arg\max_{(\beta_0,\beta)} \frac{1}{n}\sum_{i=1}^{n} d_i \log(\Phi(\beta_0 + \beta' x_i)) + \qquad (2)\\ (1 - d_i) \log(1 - \Phi(\beta_0 + \beta' x_i))\end{aligned}$$

which is easily solved by nonlinear maximization and gives consistent, asymptotically normal estimates with consistently-estimated standard errors, see, e.g., Greene (2000). The empirical results will be presented in the next section. Readers who are not interested in the econometric technicalities required to allow nonlinearity in the decision index (1) may wish to skip ahead to that section.

3.2 Nonparametric Estimation of the Link between Loan-to-Value and Default

A potential weakness of standard probit, in our application, is the assumption of a linear decision index (1). Options pricing theory predicts that the put-option component of the value of default depends nonlinearly upon the loan-to-value ratio. The exact nonlinear shape is not possible to derive due to the complexity of the embedded put option. The put-option-based value of default is near zero for loan-to-value below one and then slopes positively. There is corresponding empirical evidence from US research that strategic mortgage default is nonlinear in the loan-to-value ratio, which again argues against the linearity assumption in the decision index.

In this subsection we analyze a probit model with a fully nonparametic decision index. This model is theoretically estimable by maximum likelihood, see Matzkin (1992), but it is not feasible in our application due to the curse of dimensionality (we have six explanatory variables). Nonetheless we can use the general model to estimate the conditional expected rate of default as a function of loan-to-value. This conditional expectation function is estimable, and can be compared to the predicted conditional expectation function implied by the linear-index probit model. Comparison of the two estimates of this conditional expectation function provides the basis for a nonparametric test of index-linearity of the probit model. We are able to test the linear-index probit model against a general nonparametric alternative without being able to completely estimate the nonparametric alternative.

We replace the linear decision index with a nonlinear generalization:

$$v_i = f(x_i) + \varepsilon_i \tag{3}$$

where $f(\cdot)$ is a thrice continuously differentiable multivariate function. We continue to assume that ε_i has a standard normal distribution and is independent across i. We assume that for each i the vector of explanatory variables x_i is a realization from a multivariate joint distribution, independent of ε_i :

$$x_i \sim D,$$

with the restrictions on D described later. Let the first component of x_i, that is x_{1i}, be the loan-to-value ratio. Note that conditional upon a realized value of x_i and given knowledge of $f(\cdot)$, the probability distribution for d_i has the same form as in the case of linear-index probit:

$$\Pr(d_i = 1) = \Phi(f(x_i)),$$

recall that $\Phi(\cdot)$ denotes the cumulative normal probability function. Since d_i is a binomial zero-one this implies:

$$E[d_i|x_i] = \Phi(f(x_i)).$$

Recall that we assume that $f(\cdot)$ is a smooth multivariate function. We require that the joint density of the explanatory variables, D, is sufficiently smooth so that the following conditional expectation is well-defined and thrice continuously differentiable in x_{i1}:

$$g(x_{1i}) = E[E[d_i|x_i]|x_{1i}] = E[\Phi(f(x_i))|x_{1i}]. \tag{4}$$

Nonparametric regression provides a natural method for estimating $g(x_{1i})$ based on the conditional moment expression (4). In large samples, the conditional expected default at a particular point $\overline{x}_{1i}$ is consistently estimated by the local-weighted average default in the neighbourhood of $\overline{x}_{1i}$:

$$p\lim_{n\to\infty} \frac{1}{S_n} \sum_{j=1}^{n} d_j \kappa(x_{1j}, \overline{x}_{1i}) = g(\overline{x}_{1i}) \tag{5}$$

where $\kappa(x_{1j}, \overline{x}_{1i}) = dens(\frac{x_{1j}-\overline{x}_{1i}}{h_n})$ for some density function $dens(\cdot)$ and bandwidth h_n, and sum of weights $S_n = \sum_{j=1}^{n} d_j \kappa(x_{1j}, \overline{x}_{1i})$. See the Technical Appendix for conditions guaranteeing the consistency and asympotic normality of the estimator (5).

Note that this fully nonparametric model encompasses the linear-index probit model as a special case. This allows us to test the linear decision index against a fully nonlinear alternative without maximum likelihood estimation of (3). First estimating the linear index probit model by maximum likelihood (2), we then use the same kernel regression to estimate the conditional expectation function using the estimated linear index probit model. Any difference between these two nonparametric estimates of the conditional expectations function captures a linear model bias of the probit model. Under the joint assumptions of this subsection and of the probit model in subsection 3.1 above:

$$p\lim_{n\to\infty}\frac{1}{S_n}\sum\Phi(\widehat{\beta}_0+\widehat{\beta}'x_j)\kappa(x_{1j},x_{1i})=g(\overline{x}_{1i}) \tag{6}$$

where the kernel regression terms are identical to (5) above. See the Technical Appendix for conditions guaranteeing consistency of the estimator (6). The difference between the unrestricted (5) and restricted (6) estimates of $g(x_{1i})$ we call the linear model bias.

3.3 Partially Linear Index Probit: A Brief Review

There are a number of semiparametric extensions of the standard linear probit model, designed to add flexibility to the functional form without unduly sacrificing estimation accuracy. The partially linear index probit model is a particulary appropriate model choice in our application. It sacrifices some of the flexibility of the fully nonparametric model discussed in the last subsection, by imposing linearity for all but one of the explanatory variables. The decision index is assumed to take the following additive semiparametric form:

$$v_i=f(x_{1i})+\beta'_{(1)}x_{(1)i}+\varepsilon_i \tag{7}$$

where $x_{(1)i}$ is a $(k-1)-$vector of the explanatory variables excluding the loan-to-value ratio x_{1i} and $\beta_{(1)}$is a $(k-1)-$vector of associated linear coefficients. The univariate function $f(x_{1i})$ is assumed to be thrice continuously differentiable, and ε_i is standard normal. The intercept β_0 is not included in the model since it is not identifiably separable from $f(x_{1i})$.

We follow the estimation algorithm proposed by Carroll, et al. (1997). To get initial values, the linear-index probit model (1) is estimated by maximum likelihood (2). Then for a grid point $\overline{x}_{1i}$ a local quasi-maximum likelihood problem is solved for scalar estimate $\widehat{f}_{\overline{x}_{1i}}$:

$$\begin{aligned}\widehat{f}_{\overline{x}_{1i}}=\arg\max\frac{1}{S_n}\sum_{i=1}^{n}\kappa(x_{1i},\overline{x}_{1i})\{d_i\log(\Phi(\widehat{f}_{\overline{x}_{1i}}+\widehat{\beta}'_{(1)}x_{(1)i}))+\\(1-d_i)\log(1-\Phi(\widehat{f}_{\overline{x}_{1i}}+\widehat{\beta}'_{(1)}x_{(1)i}))\}\end{aligned} \tag{8}$$

where $\kappa(x_{1i},\overline{x}_{1i})$ is a kernel-weighting scheme and S_n is the sum of the kernel weights. This local quasi-maximum likelihood problem is solved for each of a set of finely spaced grid points covering the sample range of x_{1i}. A cross-section of implied estimates for $f(x_{1i})$ is found by interpolating between grid points:

$$\widehat{f}(x_{1i}) = \widehat{f}_{\overline{x}_{1i}} + (x_{1i} - \overline{x}_{1i})(\widehat{f}_{\overline{x}^*_{1i}} - \widehat{f}_{\overline{x}_{1i}}) \tag{9}$$

where $\overline{x}^*_{1i} > \overline{x}_{1i}$ are the two contiguous grid points containing x_{1i}. Next, we return to the linear-index probit maximum likelihood problem but replacing $\beta_0 + \beta_1 x_{1i}$ with the pre-estimated $\widehat{f}(x_{1i})$ from (9):

$$\widehat{\beta}_{(1)} = \arg\max_{\beta_{(1)}} \frac{1}{n}\sum_{i=1}^{n} d_i \log(\Phi(\widehat{f}(x_{1i}) + \beta'_{(1)}x_{(1)i}))+ \tag{10}$$
$$(1-d_i)\log(1-\Phi(\widehat{f}(x_{1i}) + \beta'_{(1)}x_{(1)i})).$$

The two steps (8) and (10) are iterated to convergence. See Carroll, et al. (1997) and Bellemare, et al. (2002) for discussion of convergence properties, optimal bandwidth choice, and related issues. Our estimates appear in the next section.

4 Empirical Analysis of Irish Mortgage Defaults

4.1 The Database and Key Variables

Our database was provided by Permanent TSB bank and consists of all property loans at Permanent TSB that have submitted a Standard Financial Statements (SFS). The bank collates the information in the SFS with existing bank information on the loan account, including application information and payment records.

The Central Bank of Ireland mandates that all mortgage lenders must collect an SFS from each home loan mortgage borrower in arrears, as part of the Mortgage Arrears Resolution Process (MARP). MARP is the Central Bank mandated process that all regulated mortgage lenders must follow in dealing with customer mortgage payment difficulties. Each regulated mortgage lender must treat every loan which has been arrears of any amount for more than 31 calendar days as in MARP and must write to the mortgage borrower within 3 business days after these 31 days are elapsed and tell them that they are covered by MARP. The lender must provide an SFS to the borrower in

MARP, give them assistance in filling out the SFS as needed, and then must pass the completed SFS to the Arrears Support Unit within the lending bank which must follow specific regulations in dealing with each MARP case. If the mortgage borrower fails to return the SFS then they can be classified under Central Bank of Ireland regulations as a noncooperative borrower and borrower protections under MARP may be lifted. Mortgage borrowers may also voluntarily submit an SFS, for example in order to negotiate mortgage restructuring without falling into arrears.

There are a total of 28,377 loan accounts in the database, 25,235 home loan accounts and 3,142 residential property investor loan accounts (called buy-to-let loans). Mortgage borrowers with both home and buy-to-let loans are included in the buy-to-let loans figure. For each multiple-loan account we aggregate the individual loan characteristics and effectively treat it as one loan observation. Taking account of borrowers with multiple loans the database covers 37,547 individual home loans and 4,285 individual buy-to-let loans; this compares to a total outstanding portfolio of 140,060 home loans and 23,133 buy-to-let loans at Permanent TSB, so 23.7% of the bank's total home loans portfolio are in the database and 18.5% of its buy-to-let loans portfolio. The database includes a default dummy for any loan that has accumulated arrears of greater than 90 days. A multiple account is treated as in default if accumulated arrears on any of the loans is greater than 90 days of required payments. Table 1 shows the percentages of the two loan types in default in the database. In the Permanent TSB total loan book, 15.3% of home loans and 17.9% of buy-to-let loans are in default; this of course differs sharply from our database (SFS-linked loans only) with 48.7% for home loans and 49.9% for buy-to-let loans in default.

In addition to the default dummy, the database has the "number of days" of accumulated arrears (30 x arrears amount/monthly required payment). Table 2 summarizes this data. This measure has the advantage over the default dummy that it captures the level of accumulated arrears rather than only giving a binary indicator of default. However, the range of values runs very high - half of the mortgages in arrears have almost a year (314 days) of accumulated arrears. The difference between a loan that is five years in arrears and a loan which is one year in arrears seems mostly a matter of timing for when the default began, rather than a different decision by the mortgage borrower. Also, there is extant research literature on mortgage loan default but no comparable non-Irish data or research on multi-year accumulated arrears. Hence we focus on models explaining loan default rather than accumulated arrears.

There are two sources of censoring in our database, both of which limit the general applicability of our empirical analysis. First, we only have information on mortgages for which there is an SFS on file at the bank. Completely non-distressed mortgages do not appear in our database, and so we do not model their holders' decision-making in choosing non-default.

The second source of censoring comes from imperfect compliance with the Central Bank of Ireland requirement for an SFS for each troubled mortgage. It is not possible from the database to compute the compliance rate for all mortgage types since SFS submissions can be required by the bank or voluntarily chosen by the mortgage borrower. One exception is home mortgages in default, where submission of an SFS is mandated in all cases by MARP. Permanent TSB records 21,398 home loan accounts in default, but they have only 14,996 SFS submissions from home loan mortgage borrowers in default, giving a SFS submission compliance rate of 70.1% for this subcategory. The potential statistical interaction between the non-cooperation decision of mortgage borrowers in arrears and our model of their mortgage default decision (based only on data for those who have complied) limits the applicability of our results for mortgages outside the conditioning set. It seems possible that non-cooperation is more tempting for borrowers with certain characteristics, and these characteristics may also impact their default decision-making. We can only offer the caveat that our model is of borrower default outcomes conditional upon their submitting an SFS, and is not dependable for non-cooperating borrowers, who are outside this conditioning set.

We rely on six explanatory variables for loan default. Application LTV is the loan-to-value ratio at the time the loan was issued (we also have the date of issue, which we use in Table 3 below). LTV is the estimated current loan to value ratio. The current loan to value ratio takes the most recent physical valuation of the property available to the bank (for the majority of loans this will be the valuation done at the application date, but it may be more recent) and then uses a property price index to adjust forward the valuation to account for price increases and/or decreases since the physical valuation date. The forward price adjustment uses the most relevant of the following four property price indices for each individual property: Dublin houses, Dublin apartments, non-Dublin houses, and non-Dublin apartments. The loan amount is adjusted for amortization or reverse-amortization of the capital balance using the bank's payment records on the individual loan.

The payment to income index, or affordability index for short, is defined as required payment commitments divided by net income. Net income is the after-tax income of the borrower (or multiple borrowers). The definition of required payment commitments differs between home loans and buy-to-let loans:

Required payment commitments for home loans = existing short term debt payments + existing mortgage payments + existing buy-to-let deficit + maintenance costs + proposed buy-to-let deficit + proposed mortgage payments - tax relief.

Required payment commitments for buy-to-let loans = existing short term debt payments + existing mortgage payments + existing buy-to-let deficit + maintenance + proposed buy-to-let deficit - tax relief.

The same formulas are used for the application values and current values of the affordability index. The current values are at the date on which the most recent Standard Financial Statement was received, and use information provided by the household on the SFS.

The loan-to-value ratios for a multiple-loan account are computed as the sum of the multiple loan amounts divided by the sum of the property values, both currently and at the application date of the most recent loan. The affordability ratio for a multiple-loan account sums the required payment commitments from all the loans and then divides by net income.

We examined the database for data outliers and other discernible errors. The only notable problem we could identify was that 0 had been used in some cases in place of missing data. Since all six of our explanatory variables should be strictly positive, except in most unusual circumstances, we treat all zero entries as missing. We truncated application LTV and LTV at 5.0, and the affordability index at 3.0, to dampen the influence of extreme values (which may be data errors) on the estimation routines. Table 3 shows the number of mortgage entries in our database for each year of loan origination, along with the number of data points truncated. The columns in the table differ since some variables have missing data, particularly for application data at earlier loan origination dates. Sixty-seven percent of the mortgages in the database originate in the four years 2005-2008. Table 4 provides descriptive statistics on the six explanatory variables. Table 5 shows the correlation matrix of the explanatory variables.

4.2 Estimation of the Model

As a preliminary step we double-sort all loans using each pair of the three current variables: loan-to-value, payment-to-income, and log income, and then compute the average default rate within each subset. For each variable the first breakpoint is the 25% fractile of its univariate distribution and the second breakpoint is the 75% fractile, so that the middle category captures the interquartile range. The interquartile range is $(0.62, 1.42)$ for loan-to-value, $(0.28, 0.54)$ for payment-to-income, and $(\log(1,802), \log(3,480))$ for log of net monthly income. The results appear in Table 6. All three of the variables seem to contain information about default rates. The strongest double-sort comes from using loan-to-value and log income together, but all three variables show some explanatory power. The corresponding tables for home loans and buy-to-let loans examined separately are shown in the supplementary tables in the appendix.

The results in Table 6a are particularly interesting. For purposes of informal analysis the three columns in the table can be thought of as affordable payment, stressed payment, and unaffordable payment; the three rows can be thought of as positive equity, zero to moderate negative equity, and large negative equity. Note that the $(1, 1)$ subset (affordable payment, positive equity) has an average default rate of 43.4% whereas the $(3, 3)$ subset (unaffordable payment, large negative equity) has a default rate of 70.6%. The $(3, 1)$ and $(1, 3)$ subsets have roughly equal average default rates which are not that much higher than for the $(1, 1)$ subset. The big jump in the default rate comes when the loan has *both* low affordability *and* large negative equity: the joint effect seems much bigger than the sum of the two individual effects. This conforms to Foote's (2008) dual-trigger model of default, and supports the US-based findings of Bhutta et al. (2010) and Elul et al. (2010). The probit model which we use below also captures this empirical feature.

Table 7 follows on from Table 6a. We subdivide the loans into those that have undergone a decrease in affordability since loan origination (for example due to unemployment, lower household income, or higher short-term debt obligations) and those have undergone an increase, and look at the default rates for the three levels of current loan-to-value, using the interquartile range for the middle loan-to-value category, as in Table 6. Both decreased affordability and the current loan-to-value ratio have an impact on default rates, and the two effects interact, as in Table 6.

We begin parameterized model estimation using a probit model with all six explanatory variables:

$$\text{Prob}(\text{default}_i) = \Phi(\beta_0 + \beta_1\text{LTV}_i + \beta_2\text{Afford}_i + \beta_3\text{LogIncome}_i + \beta_4\text{AppLTV}_i + \beta_5\text{AppAfford}_i + \beta_6\text{AppLogIncome}_i$$

The results are shown in Table 8, for all loans in the database, and then for the subsample of home loans and buy-to-let loans estimated separately.

Application-date affordability index and application-date log income have weak explanatory power in Table 8. In Table 9 we re-estimate the probit models dropping these two variables. In Table 10 we show estimates of this same model using the logistic distribution in place of the normal distribution. We will focus on the probit model with four explanatory variables (Table 9).

The last two columns in Table 9 show the marginal impact on default probability of a marginal change in each explanatory variable, calculated two ways: using the sample average of the other explanatory variables, and computed individually at each sample point and then averaged across the sample. Both measures are used in the literature but the latter is generally considered preferable; see Green (2000). Current log income has more impact on the default decision than the current affordability index. A strong and surprising finding is the notable power of current loan-to-value in determining Irish mortgage default decisions, as measured by these marginal probabilities. This strong relative explanatory power is further increased by the fact that current loan-to-value has a wider interquartile range than the affordability index and log income.

A key topic in the existing US research literature is measuring the proportion of mortgage defaulters which are distressed (inability to pay) versus strategic (put-optionality) defaults. The current loan-to-value ratio is the key variate in a strategic defaulter's decision calculus, whereas loan-to-value has no role in a distressed defaulter's decision calculus. The high explanatory power of current loan-to-value is evidence of strategic decision-making playing at least a partial role (explicitly or subconsciously) by Irish mortgage defaulters. The evidence indicates that Irish mortgage defaulters in our sample have mixed motives, influenced simultaneously by stressed affordability and put optionality. Any "pure" strategic defaulters, with no affordability pressure and motivated solely by put-optionality, are more likely to be in the 30% or so of non-cooperating mortgage defaulters, who do not submit an SFS and are not in our sample.

Lastly, we use nonparametric and semiparametric methods to examine potential nonlinearity in the response of default to loan-to-value. We use the Gaussian kernel throughout and set the bandwidth h using Silverman's rule of thumb, $h = (\frac{4\sigma_d^2}{3n})^{\frac{1}{5}}$,where σ_d^2 is the sample variance of observed defaults and n is the number of observations in the sample or subsample. We estimate over the range $0 <$LTV< 3 but note with caution that kernel methods are unreliable in the tails of the data range. The 99% middle range of the data, leaving 0.5% in each tail of the sample, is $(.06, 2.62)$ for all loans, $(.02, 2.28)$ for home loans, and $(.17, 3.07)$ for buy-to-let loans. Nonparametric or semiparametric estimates outside this middle range are untrustworthy.

Figure 2 shows unconditional expected default as a nonparametric function of loan-to-value using kernel-based nonparametric regression; see equation (5) in Section 3.2. Figure 3 takes the nonparametrically-estimated expected defaults from Figure 2 and compares them to the conditional expected defaults from the probit model in Table 9; see equations (3) and (5) in Section 3.2. There is evidence for the type of nonlinearity predicted by options theory in Figures 2 and 3, with the response curves flattening for LTV< 1 and curving upward at high LTV. Figure 4 shows the nonlinear LTV response functions estimated by the partially linear index probit model (see equation (7) in Section 3.2). The results are suggestive, but not definitive, regarding a convex nonlinearity in the link between loan-to-value and loan default; see Elul et al. (2010) for related evidence for the US market using different estimation methods (step-wise linearity over intervals in a logit model). The convex nonlinearity, as reflected in a nonzero linear model bias, seems to start at a loan-to-value ratio of 1.5 for home loans. For buy-to-let mortgages, the convex nonlinearity starts earlier, near a loan-to-value ratio of 1.0. The coefficient estimates for the other five variables (for which the linearity assumption is maintained) are shown in the supplementary tables in the appendix.

5 Conclusion

Following the collapse of the Irish credit/property bubble, Irish residential property prices fell sharply and mortgage arrears grew explosively. From the peak in Q2 2007, residential property prices fell 50.3% to the trough in Q2 2012, subsequently recovering 1.2% from the trough by Q2 2013. The number of home mortgages in default (greater than 90 days of accumulated arrears) grew 272.6%, from 26,271 in Q3 2009 to 97,874 in Q2 2013; as of Q2 2013, 12.7% of home loan mortgages are in default. Data on buy-to-let defaults is only available recently so the growth path is not known, but 20.4% of buy-to-let mortgages are in default as of Q2 2013.

Property price falls have been shown to have a strong causal link to household mortgage default decisions, in a wide range of studies using US data. Although property resale price has no effect on a household's ability to pay the mortgage, it has a large effect on the implicit put-option value of mortgage default. Unless the lender has unhindered recourse to the household's future income, the holder of a negative equity mortgage can effectively "put" the property to the lender and in exchange stop paying the mortgage. This put-optionality effect on mortgage default has been shown to be particulary strong when combined with household income stress. In the "dual trigger" model of mortgage default, households are particularly likely to default when household income stress is combined with large positive put-option value of default, captured by a loan-to-value ratio substantially above 1.0.

This paper confirms key US-data findings on recent Irish mortage data. We rely on a data set which only contains borrowers within the Mortgage Arrears Resolution Process who have submitted a Standard Financial Statement, so non-cooperating borrowers, and borrowers who have never experienced mortgage difficulties, are censored from the data. Within this restricted set of borrowers, the loan-to-value ratio is a very important, arguably the most important, predictor of mortgage default. Our evidence supports the dual-trigger model of default: Irish mortgage borrowers are most likely to default when income stress is combined with strong put-optionality as reflected in the loan-to-value ratio. The consensus view from US-based research is that both affordability and put-optionality affect default rates, but affordability is the more important influence. In our doubly-censored Irish sample, put-optionality is a more powerful predictor of default than affordability.

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Technical Appendix

This technical appendix contains background material on the nonparametric regression estimation procedure presented in Section 3.2. First we assume that the default decision index is fully nonparametric:

$$v_i = f(x_i) + \varepsilon_i$$

and wish the estimate the univariate nonparametric relationship between x_{1i} and expected default. Define $g(x_{1i})$ as conditional expected default:

$$g(x_{1i}) = E[d_i|x_{1i}] = E[\{f(x_i) + \varepsilon_i\}^+|x_{1i}]$$

where $\{\cdot\}^+$ equals one if the argument is positive and otherwise zero. In order to implement nonparametric kernel regression, we assume that $g(\cdot)$ is thrice continuously differentiable. This imposes implicit assumptions on the smoothness of $f(\cdot)$ and on D, the multivariate distribution of x; we take this assumption as primitive, noting in passing that there are many explicit special cases of $f(\cdot)$ and D which would justify the assumption. Let ξ_i denote the mean-zero deviation of realized default from conditional mean default:

$$d_i = g(x_{1i}) + \xi_i$$

where we assume that the density function of x_{1i} is thrice continuously differential and that ξ_i has uniformly bounded conditional variance $\sigma_\xi^2(x_{1i})$. Using the Gaussian kernel together with bandwidth $h = cn^{-\frac{1}{5}}$ to estimate $\widehat{g}(x_{1i})$ by (5), we have by Theorem 2.2 in Li and Racine (2007):

$$d\lim \sqrt{nh}(\widehat{g}(x_{1i}) - g(x_{1i}) - b(x_{1i})) \sim N(0, \frac{\sigma_\xi^2(x_{1i})}{dens(x_{1i})})$$

where $b(x_{1i})$ is a standard bias correction term; see Li and Racine, page 62.

In the restricted case, we first estimate (β_0, β) under the assumption that the multivariate probit holds, and then nonparametrically estimate $\widehat{g}(x_{1i})$ using (6) applied to the predicted default rates from the estimated probit model. We ignore the estimation error in $(\widehat{\beta}_0, \widehat{\beta})$ since it converges to zero at a faster rate than $\widehat{g}(x_{1i}) - g(x_{1i})$. The same Theorem 2.2 from Li and Racine applies in this case.

Table 1: Percentage Distributions of Loan Type and Default Rates

	All Loans	Home Loans	Buy-to-Let Loans
All Loans	100%	88.9%	11.1%
% Loans in Default in the Category	48.8%	48.7%	49.9%

Table 2: Statistical Distribution of Days in Arrears for Loan Accounts with Nonzero Arrears

	All Loans	Home Loans	Buy-to-let Loans
10% Fractile	34	34	40.6
25% Fractile	110	106	150
Median	314	305	423
Mean	451.8	443.8	516.8
75% Fractile	662	642	766.3
90% Fractile	1037	1034	1095

Table 3: Data Distribution of Each Explanatory Variable Across Years of Loan Origination

Year	Application Payment-to-Income Ratio	Application Loan-to-Value Ratio	Application Net Income	Payment-to-Income Ratio	Loan-to-Value Ratio	Net Income
1999 or earlier	5.27%	3.72%	3.08%	5.27%	5.27%	5.15%
2000	2.55%	2.55%	2.17%	2.55%	2.55%	2.48%
2001	2.75%	2.74%	2.39%	2.75%	2.75%	2.68%
2002	3.65%	3.65%	3.22%	3.65%	3.65%	3.58%
2003	5.98%	5.98%	5.89%	5.98%	5.98%	5.84%
2004	8.76%	8.76%	8.75%	8.76%	8.76%	8.61%
2005	13.92%	13.92%	13.92%	13.92%	13.92%	13.67%
2006	21.30%	21.30%	21.29%	21.30%	21.30%	20.90%
2007	19.00%	19.00%	18.88%	19.00%	19.00%	18.58%
2008	13.22%	13.22%	12.87%	13.22%	13.22%	13.00%
2009	2.83%	2.83%	2.82%	2.83%	2.83%	2.77%
2010	0.53%	0.53%	0.52%	0.53%	0.53%	0.52%
2011	0.15%	0.15%	0.15%	0.15%	0.15%	0.15%
2012	0.07%	0.07%	0.06%	0.07%	0.07%	0.07%
2013	0.02%	0.00%	0.00%	0.02%	0.02%	0.02%
Missing	13.68%	1.59%	3.98%	2.02%	0.00%	2.02%
Truncated	0.11%	0.02%	0.00%	2.45%	0.41%	0.00%

Table 4: Descriptive Statistics of Explanatory Variables

	Bottom Quartile	Median	Top Quartile	Mean	Standard deviation	Number of Observations
Application Date Loan-to-Value	.420	.640	.880	.631	.256	28061
Current Loan-to-Value	.620	1.02	1.42	1.04	.570	28377
Application Date Payment-to-Income	.290	.340	.370	.336	.141	25549
Current Payment-to-Income	.280	.380	.540	.471	.351	27879
Application Date Net Income	€2664	€3517	€4473	€3843	€3390	27725
Current Net Income	€1802	€2529	€3480	€2840	€1868	27879

Table 5: Correlation Matrix of the Explanatory Variables

	LTV	Application Date LTV	Affordability	Application Date Affordability	Log Income	Application Date Log Income
LTV	1.000					
Application Date LTV	0.655	1.000				
Affordability	0.113	0.039	1.000			
Application Date Affordability	0.081	0.020	0.109	1.000		
Log Income	0.076	0.012	-0.556	0.073	1.000	
Application Date Log Income	0.123	0.096	0.014	0.012	0.164	1.000

Table 6: Default rates for loans doubly-sorted by loan-to-value, payment-to-income and net income: Full Sample

6a: Default rates for loans sorted by loan-to-value and affordability

	Low Payment-to-Income	Moderate Payment-to-Income	High Payment-to-Income
Low LTV	43.43%	39.04%	46.03%
Moderate LTV	41.55%	43.98%	57.34%
High LTV	47.40%	56.47%	70.55%

6b: Default rates for loans sorted by loan-to-value and net income

	High Income	Moderate Income	Low Income
Low LTV	31.91%	40.26%	48.85%
Moderate LTV	39.11%	47.40%	56.63%
High LTV	51.34%	59.78%	69.13%

6c: Default rates for loans sorted by affordability and net income

	High Income	Moderate Income	Low Income
Low Payment-to-Income	38.40%	42.02%	51.39%
Moderate Payment-to-Income	45.11%	47.31%	60.27%
High Payment-to-Income	58.50%	48.36%	60.81%

Table 7: Proportions of Loans in Default for Subcategory of Loan-to-value and Increased/Decreased Affordability

Loan Type	Change in Affordability	Low Loan-to-value	Moderate Loan-to-value	High Loan-to-value
Full Sample	Increased Affordability	31.00%	40.89%	49.92%
	Decreased Affordability	37.41%	49.48%	63.83%
Home Loans	Increased Affordability	31.09%	41.49%	50.72%
	Decreased Affordability	37.72%	49.18%	63.56%
Buy-to-Let Loans	Increased Affordability	28.07%	33.03%	41.63%
	Decreased Affordability	33.33%	51.16%	65.93%

Table 8: Probit Model of Default with Six Explanatory Variables

8a: Full Sample

Variable	Coefficient	Std Error	T-Stat	Significance
App Affordability	-0.063	0.058	-1.081	0.280
App LTV	-0.617	0.043	-14.261	0.000
App Log Income	0.016	0.011	1.471	0.141
Affordability	0.312	0.031	10.170	0.000
LTV	0.620	0.022	28.443	0.000
Log Income	-0.192	0.019	-10.310	0.000
Constant	0.901	0.159	5.664	0.000
Pseudo R-squared	0.059			
Number of observations	25116			

8b: Home Loans

Variable	Coefficient	Std Error	T-Stat	Significance
App Affordability	-0.078	0.066	-1.184	0.236
App LTV	-0.619	0.046	-13.531	0.000
App Log Income	0.019	0.021	0.895	0.371
Affordability	0.225	0.043	5.274	0.000
LTV	0.628	0.023	26.865	0.000
Log Income	-0.207	0.026	-7.965	0.000
Constant	1.024	0.197	5.200	0.000
Pseudo R-squared	0.054			
Number of observations	22474			

8c: Buy-to-Let Loans

Variable	Coefficient	Std Error	T-Stat	Significance
App Affordability	0.043	0.135	0.318	0.750
App LTV	-0.564	0.143	-3.930	0.000
App Log Income	0.021	0.013	1.663	0.096
Affordability	0.551	0.068	8.132	0.000
LTV	0.578	0.063	9.135	0.000
Log Income	-0.205	0.048	-4.222	0.000
Constant	0.772	0.438	1.763	0.078
Pseudo R-squared	0.115			
Number of observations	2642			

Table 9: Probit Model of Default with Four Explanatory Variables

9a: Full Sample

Variable	Coefficient	Std Error	T-Stat	Significance	Marginal probability at average values	Average of pointwise marginal probability
App LTV	-0.394	0.039	-10.096	0.000	-0.15694	-0.2069
Affordability	0.227	0.027	8.312	0.000	0.09028	0.11901
LTV	0.452	0.019	23.857	0.000	0.18012	0.23744
Log Income	-0.237	0.017	-14.331	0.000	-0.09427	-0.12427
Constant	1.484	0.136	10.932	0.000		
Pseudo R-squared	0.044					
Number of observations	27568					

9b: Home Loans

Variable	Coefficient	Std Error	T-Stat	Significance	Marginal probability at average values	Average of pointwise marginal probability
App LTV	-0.383	0.041	-9.292	0.000	-0.15243	-0.19891
Affordability	0.093	0.036	2.565	0.010	0.03689	0.04814
LTV	0.458	0.020	22.585	0.000	0.18248	0.23813
Log Income	-0.275	0.021	-13.239	0.000	-0.10964	-0.14307
Constant	1.825	0.170	10.725	0.000		
Pseudo R-squared	0.039					
Number of observations	24515					

9c: Buy-to-Let Loans

Variable	Coefficient	Std Error	T-Stat	Significance	Marginal probability at average values	Average of pointwise marginal probability
App LTV	-0.425	0.131	-3.247	0.001	-0.16893	-0.19999
Affordability	0.491	0.058	8.502	0.000	0.19534	0.23126
LTV	0.483	0.056	8.588	0.000	0.19204	0.22735
Log Income	-0.210	0.042	-4.974	0.000	-0.08373	-0.09912
Constant	1.089	0.379	2.875	0.004	0.43316	0.5128
Pseudo R-squared	0.102					
Number of observations	3053					

Table 10: Logit Model of Default with Four Explanatory Variables

10a: Full Sample

Variable	Coefficient	Std Error	T-Stat	Significance
App LTV	-0.724	0.066	-10.954	0.000
Affordability	0.361	0.046	7.875	0.000
LTV	0.797	0.034	23.335	0.000
Log Income	-0.406	0.027	-14.922	0.000
Constant	2.572	0.223	11.545	0.000
Pseudo R-squared	0.046			
Number of observations	27568			

10b: Home Loans

Variable	Coefficient	Std Error	T-Stat	Significance
App LTV	-0.712	0.070	-10.193	0.000
Affordability	0.125	0.060	2.085	0.037
LTV	0.811	0.037	22.069	0.000
Log Income	-0.467	0.034	-13.703	0.000
Constant	3.123	0.279	11.211	0.000
Pseudo R-squared	0.040			
Number of observations	24515			

10c: Buy-to-Let Loans

Variable	Coefficient	Std Error	T-Stat	Significance
App LTV	-0.738	0.217	-3.393	0.001
Affordability	0.843	0.102	8.286	0.000
LTV	0.860	0.100	8.601	0.000
Log Income	-0.407	0.073	-5.543	0.000
Constant	2.225	0.649	3.430	0.001
Pseudo R-squared	0.106			
Number of observations	3053			

Tables Appendix

Table A.1: Default rates for loans doubly-sorted by loan-to-value, payment-to-income and net income: Home loans

A.1.a: Default rates for loans sorted by loan-to-value and affordability

	Low Payment-to-Income	Moderate Payment-to-Income	High Payment-to-Income
Low LTV	43.70%	39.44%	45.77%
Moderate LTV	42.70%	44.57%	56.97%
High LTV	48.40%	56.84%	70.69%

A.1.b: Default rates for loans sorted by loan-to-value and net income

	High Income	Moderate Income	Low Income
Low LTV	32.70%	40.11%	48.63%
Moderate LTV	38.67%	46.83%	55.69%
High LTV	51.08%	59.41%	67.97%

A.1.c: Default rates for loans sorted by affordability and net income

	High Income	Moderate Income	Low Income
Low Payment-to-Income	39.37%	43.08%	45.69%
Moderate Payment-to-Income	45.28%	47.43%	59.59%
High Payment-to-Income	58.59%	48.32%	59.66%

Table A.2: Default rates for loans doubly-sorted by loan-to-value, payment-to-income and net income: Buy-to-let loans

A.2.a: Default rates for loans sorted by loan-to-value and affordability

	Low Payment-to-Income	Moderate Payment-to-Income	High Payment-to-Income
Low LTV	33.78%	31.21%	47.89%
Moderate LTV	27.95%	37.50%	58.35%
High LTV	39.10%	51.53%	70.04%

A.2.b: Default rates for loans sorted by loan-to-value and net income

	High Income	Moderate Income	Low Income
Low LTV	27.49%	43.90%	57.14%
Moderate LTV	40.29%	53.44%	69.85%
High LTV	52.15%	64.78%	85.00%

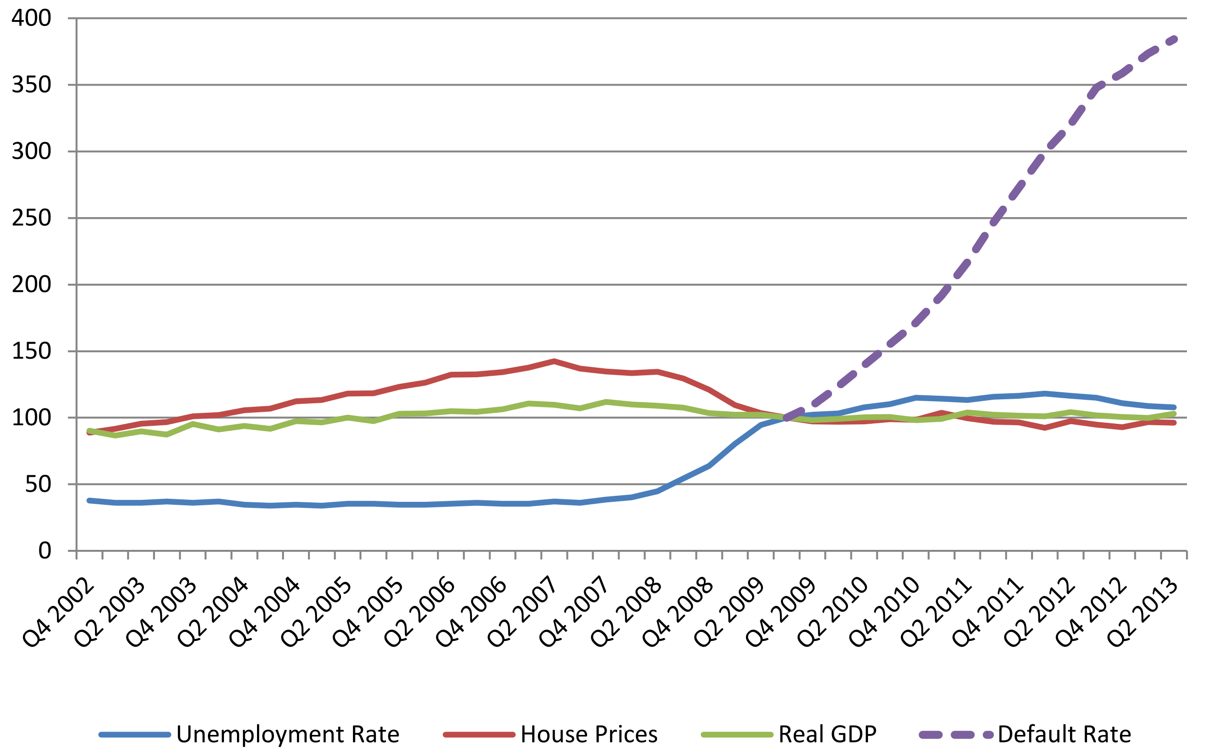
A.2.c: Default rates for loans sorted by affordability and net income

	High Income	Moderate Income	Low Income
Low Payment-to-Income	31.44%	38.29%	53.08%
Moderate Payment-to-Income	36.07%	43.94%	62.06%
High Payment-to-Income	50.00%	51.85%	73.86%

Table A.3: Partially-linear Index Probit Model of Default with Four Explanatory Variables

	Full Sample		Home Loans		Buy-to-Let Loans	
Variable	Estimated Coefficient with Standard Probit	Estimated Coefficient with Partially Linear Index Probit	Estimated Coefficient with Standard Probit	Estimated Coefficient with Partially Linear Index Probit	Estimated Coefficient with Standard Probit	Estimated Coefficient with Partially Linear Index Probit
App LTV	-0.394	-0.471	-0.383	-0.466	-0.425	-0.434
Affordability	0.227	0.227	0.093	0.086	0.491	0.497
LTV	0.452	Nonparametric	0.458	Nonparametric	0.483	Nonparametric
Log Income	-0.237	-0.241	-0.275	-0.283	-0.210	-0.217
Constant	1.484	N/A	1.825	N/A	1.089	N/A

Figure 1: Comparative Time Series of Irish Residential Property Price Index, Unemployment Rate, Per-capital Real Income and Home Loan Default Rate



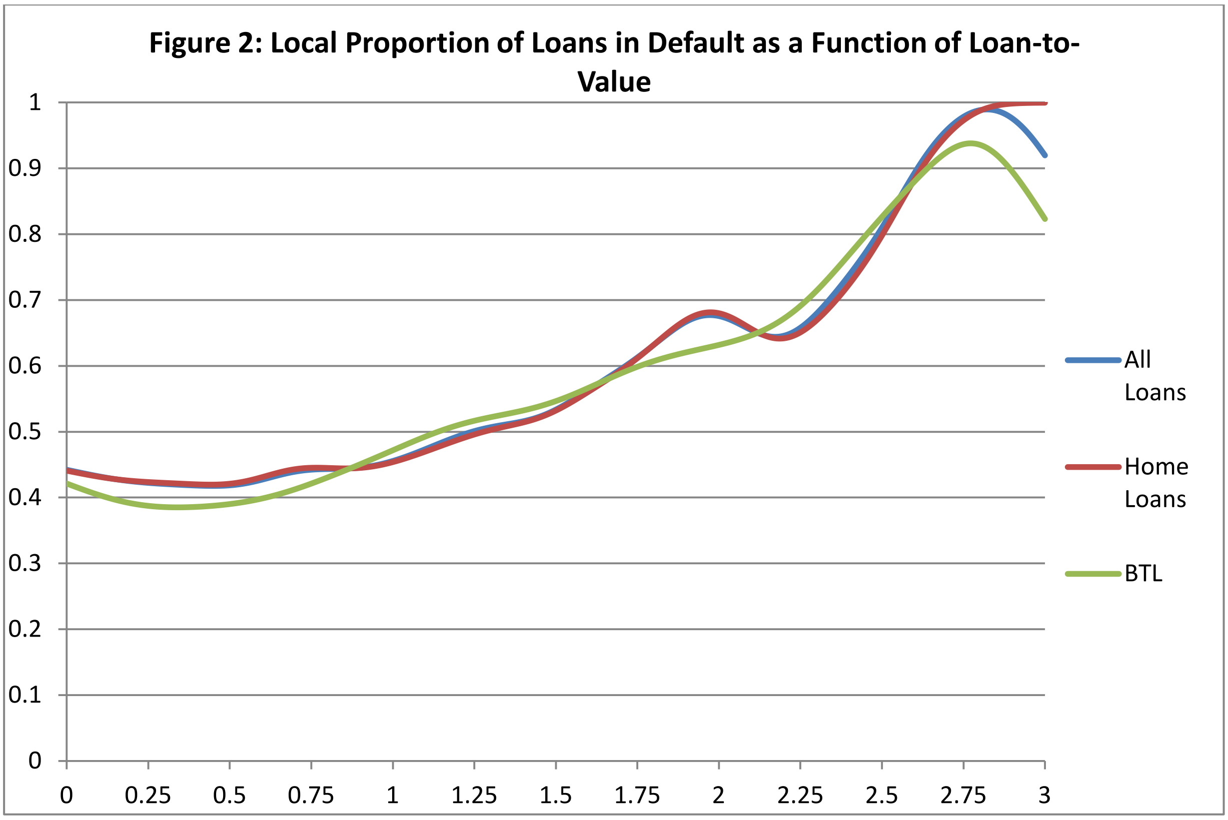
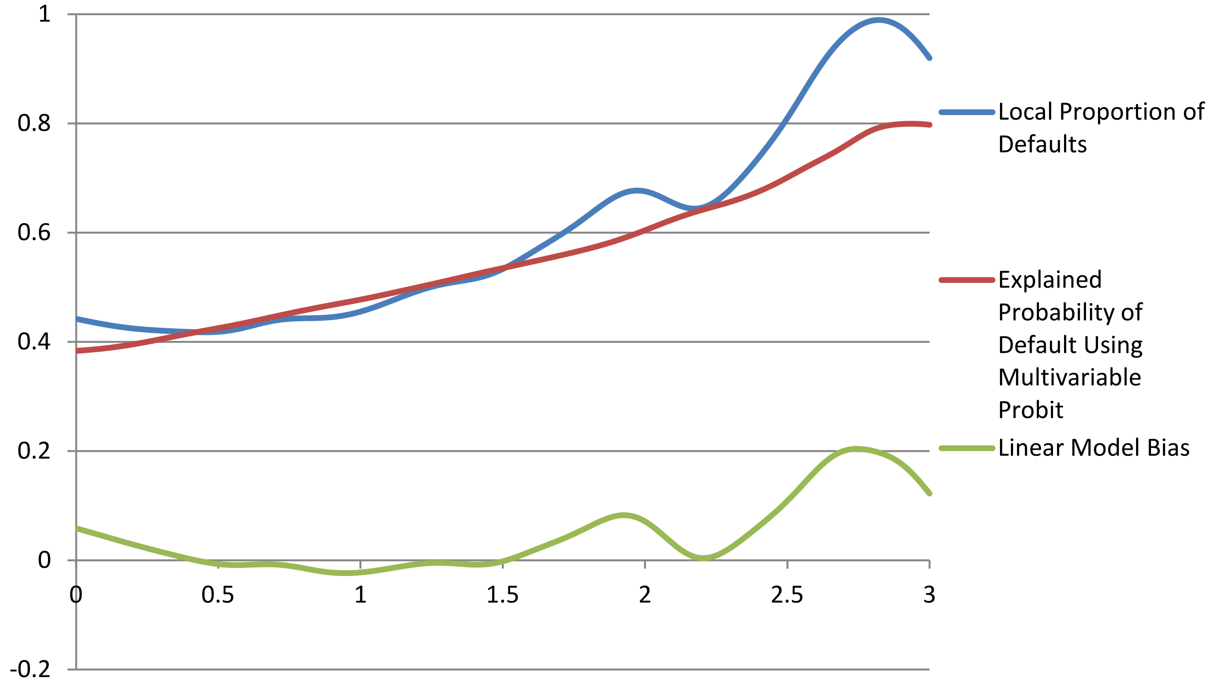


Figure 2: Local Proportion of Loans in Default as a Function of Loan-to-Value
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
0
0.25
0.5
0.75
1
1.25
1.5
1.75
2
2.25
2.5
2.75
3
All Loans
Home Loans
BTL

Figure 3a: Restricted and Unrestricted Nonparametric Estimation of the Probability of Default as a Function of Loan-to-Value, All Loans



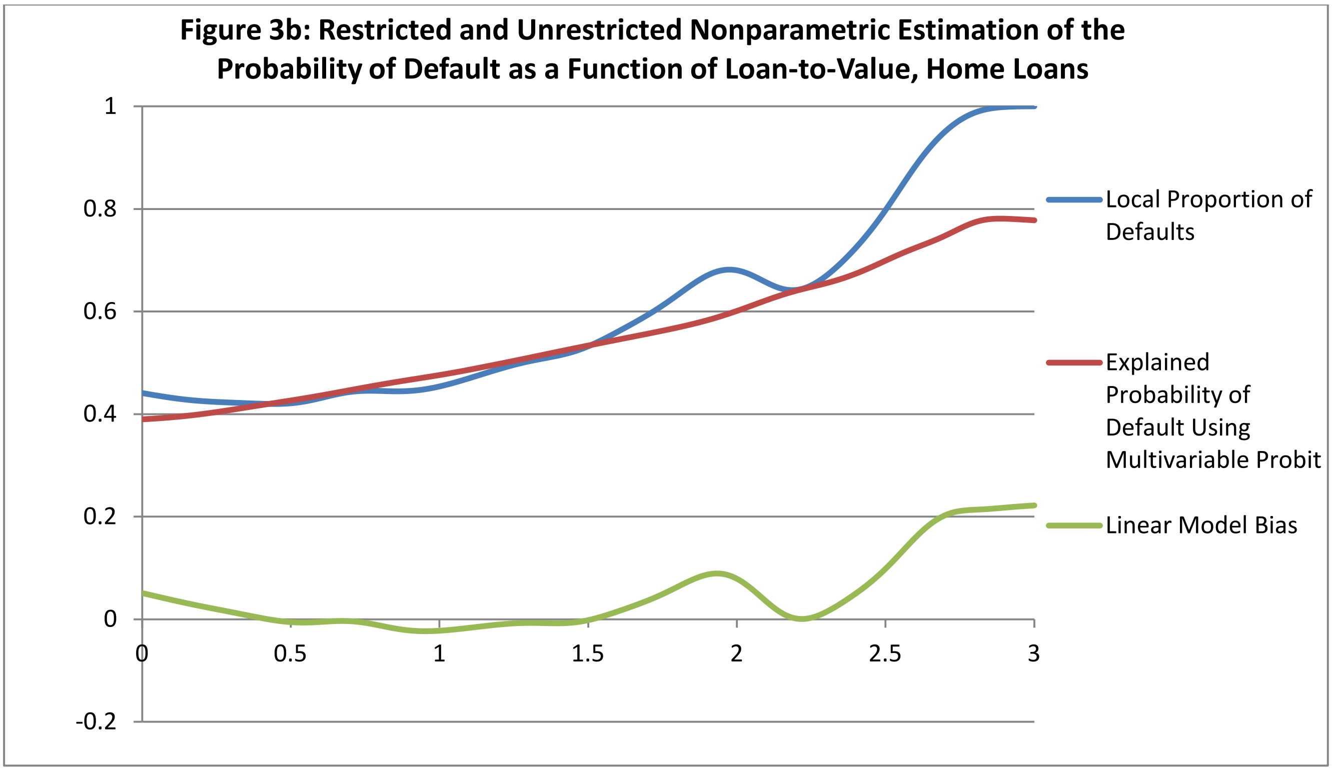


Figure 3b: Restricted and Unrestricted Nonparametric Estimation of the Probability of Default as a Function of Loan-to-Value, Home Loans
1
0.8
0.6
0.4
0.2
0
-0.2
0
0.5
1
1.5
2
2.5
3
Local Proportion of Defaults
Explained Probability of Default Using Multivariable Probit
Linear Model Bias

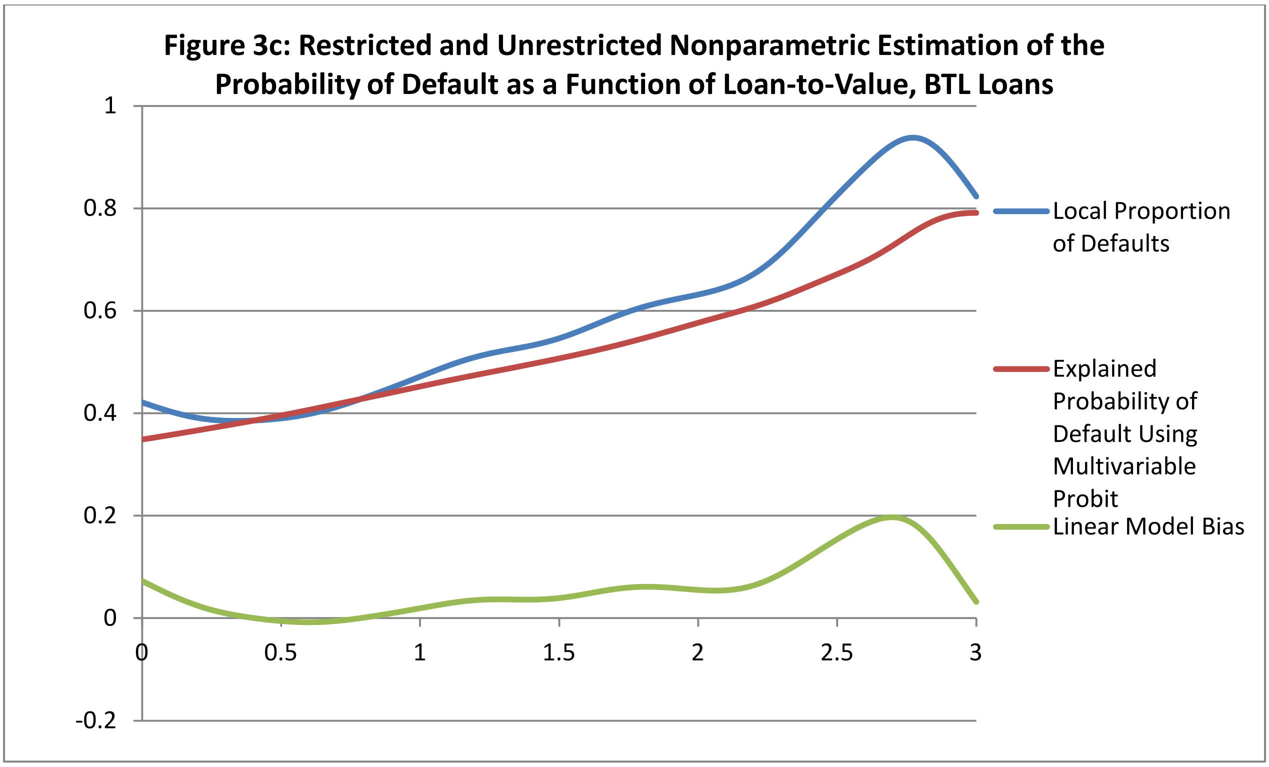


Figure 3c: Restricted and Unrestricted Nonparametric Estimation of the Probability of Default as a Function of Loan-to-Value, BTL Loans
1
0.8
0.6
0.4
0.2
0
-0.2
0
0.5
1
1.5
2
2.5
3
Local Proportion of Defaults
Explained Probability of Default Using Multivariable Probit
Linear Model Bias

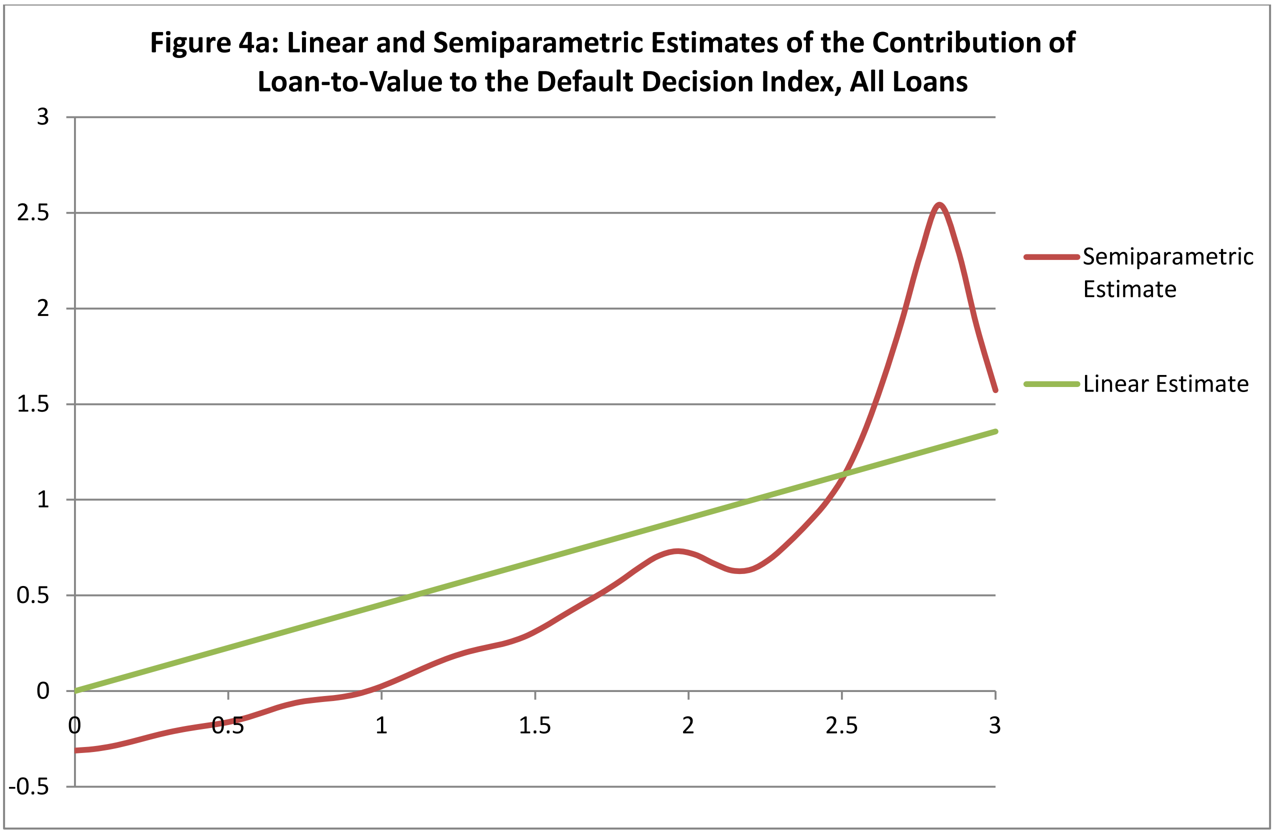


Figure 4a: Linear and Semiparametric Estimates of the Contribution of Loan-to-Value to the Default Decision Index, All Loans
3
2.5
2
1.5
1
0.5
0
-0.5
0
0.5
1
1.5
2
2.5
3
Semiparametric Estimate
Linear Estimate

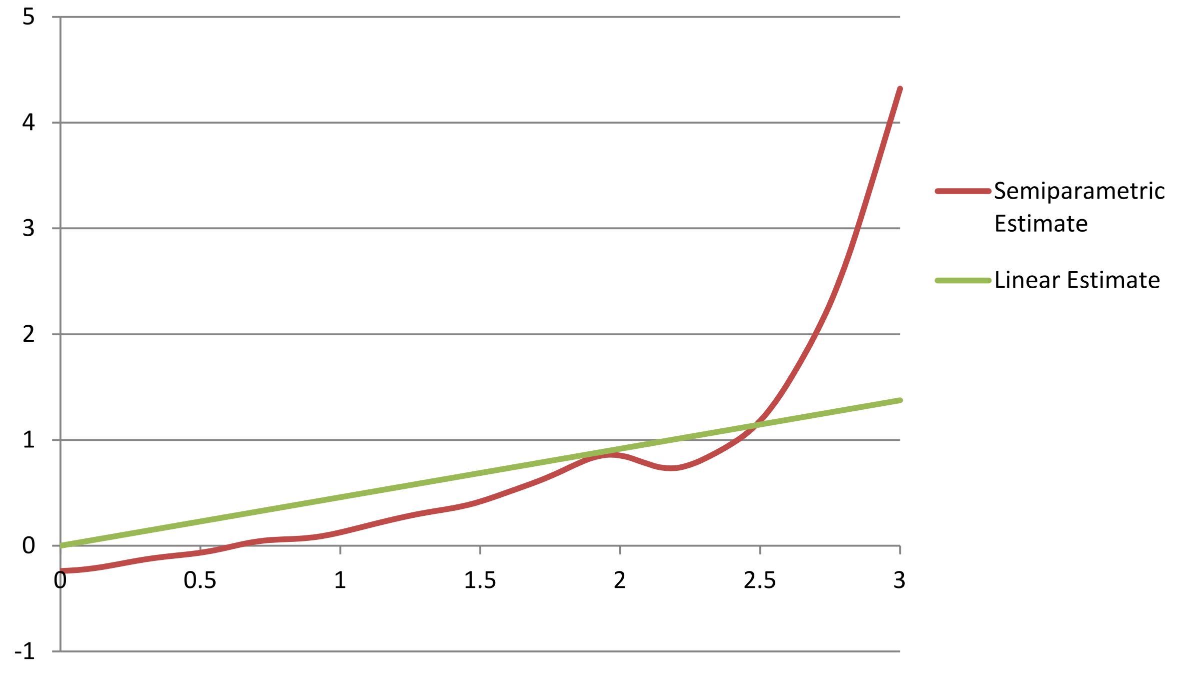


Figure 4b: Linear and Semiparametric Estimates of the Contribution of Loan-to-Value to the Default Decision Index, Home Loans

Figure 4c: Linear and Semiparametric Estimates of the Contribution of Loan-to-Value to the Default Decision Index, Buy-to-Let Loans