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Abstract

We have assembled a unique loan-level performance dataset for mortgages originated in the UK to study the differences in default likelihood between loans of varying borrower and loan characteristics. We can broadly confirm the relevance of most commonly known risk-factors and find that most drivers of default for prime are also relevant for non-conforming, drivers of repossessions are largely similar to drivers of arrears and information on adverse borrower information dominates any other risk factor. Our study provides many more details and compares results with recent studies for the US and other European countries.

Keywords: residential mortgages, loan defaults, consumer behaviour, logistic regression, United Kingdom

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1 INTRODUCTION

The global recession which started with the deterioration of the US subprime mortgage market late 2006 has expanded into virtually every developed country in the world. Particularly, most of the once booming housing markets across the globe have now undergone a severe period of distress, with most countries reporting decline in house prices, increase in mortgage defaults and contraction of the house building sector. While the economic stress poses significant strain to both institutions as well as individuals, the downturn environment also creates opportunities to study financial behaviour under exceptional situations. These studies are important to understand financial market behaviour and develop effective risk modelling and risk control procedures. This paper focuses on default behaviour in the UK mortgage market, during the recent period of economic stress.

Public studies on stress in the mortgage market have largely been limited by data availability. Studies for European markets have mainly drawn on aggregate data from national account statistics and longitudinal panel data. They focus on identifying the impact of select indicators of default, particularly the degree of equity of the borrowers they hold in their properties and the ability to pay ongoing mortgage instalments. The data limitations typically allow only for a time-series analysis on aggregate information; e.g. explaining market-wide default rates with national level equity holdings and average mortgage affordability. Other macro-economic indicators are also taken into account, such as GDP growth and the unemployment rate. The alternative of using panel data has its limitations in the limited number of risk indicators that are typically tracked in longitudinal surveys. Especially product features of the mortgage loans are rarely available from these data sets.

Studies on loan-level accounts specifically designed to identify mortgage risk drivers are more effective in providing insights into relative default risks. Studies on this type of data have mainly been limited to the US where historical performance data on a loan-level are compiled and made available to the public by third-party institutions. The availability of such data is largely determined by the regulatory framework, in particular data protection regulation and data sharing conventions. The data sets available for the US contain detailed information for a large set of loans well representing the overall market as well as all major regional areas and product types and provide a history of performance over more than a decade. This is not yet available for any European mortgage market. Our study attempts to arrive at a similar depth of insight for the UK with a dataset that comes as close to the information available in the US as possible.

We have assembled a unique loan-level performance dataset for mortgages originated in the UK to study the differences in default likelihood between loans of varying characteristics such as borrower type (e.g. self-employment, adverse credit information, etc.) and various different product types (e.g. self-certification, loan-to-value ratio, interest rate, buy-to-let, etc.). Data comprise loan-originations from prime and non-conforming lenders over the period 2004 to 2007 with default information available up until March 2009. Since the majority of default observations relate to the period after the onset of the credit crisis in the second half of 2007 our study distinctly focuses on drivers of relative risk during a period of economic stress, during which

GDP contracted and unemployment rose. It does not attempt at identifying macro-economic indicators for the prediction of market-wide default rates.

Our study provides useful insight into the drivers of default among UK mortgages under a distressed economic environment. In a first step it provides valuable insight into typical characteristics that are particularly correlated with default. We then also show via a multivariate logistic regression to what degree patterns identified in the univariate analysis of risk drivers remain valid when considering the simultaneous interaction of those risk factors. In addition, we compare the result from the prime sector with those from the non-conforming sector and find that apart from the indicators of adverse credit (which are unique to the non-conforming sector) the major default drivers are broadly the same. For the non-conforming sector we also compare results from delinquencies with those from repossessions and thereby draw conclusions about the relative likelihood of a loan curing once it has fallen into delinquency and differentiate by borrower and product type.

1.1 Key findings

Our key findings can be summarised as follows:

- Most drivers of default for prime are also relevant for non-conforming (e.g. original loan-to-value ratio, debt-to-income ratio, interest-only loans, self-employment).
- An exception seems to be fast track mortgages in the prime sector which do not appear generically more risky than income verified loans, while self-certification mortgages in the non-conforming sector invariably turn out more risky than those originated with certified income. On these grounds it looks doubtful that fast track processing in UK prime lending is generically comparable to self-certification in the non-conforming sector.
- Drivers of repossessions are largely similar to drivers of arrears, though some variables (such as the debt-to-income ratio) seem to have lower explanatory power on repossessions while others have higher explanatory power (buy-to-let and right-to-buy).
- Adverse borrower information dominates any other risk factor. This is consistent with the market convention to separate prime from non-conforming originations.
- Despite the limited time span of our data history we can also identify some trends of risk indicators over time. For example, we clearly see problems with new build properties for the vintages 2006 and 2007 (which can be attributed to a loosening of underwriting procedures) and an increasing impact of self-employment on defaults (which can be attributed to self-employed individuals being more vulnerable to general economic deterioration compared to employees).

1.2 Literature Review

Most of the studies reviewed in this section focus on aggregate macro level data to explain underlying default rates. Some of them also focus on direct causes of default (such as divorce or illness) rather than identifying predictive risk factors available long before the default event. In contrast to these studies we use a proprietary loan-level dataset on the performance of mortgages originated in the UK non-conforming and the prime sector between 2004 and 2007. The time period also allows us to investigate changes in underwriting procedures that may have increased the riskiness of particular products over time and contributed to defaults in the current crisis. Most of the UK based literature that we are aware of dates back to repossessions in the 1990s recession (e.g. Figuera, Glen and Nellis, 2005).

Many UK studies using macroeconomic data identify key drivers of mortgage default to be interest rates, unemployment, marriage breakdowns, small business failure, income and expenditure problems (see for example, Doling, Ford and Stafford, 1998; Ford, Kempson and Wilson, 1995). There are some studies however that focus more on systematic differences between borrowers in terms of equity or the level of debt they have acquired to explain default behaviour. This literature generally focuses on two competing theories of mortgage default drivers.[4] The first is termed 'equity' theory and is based on the willingness to pay. The borrower's perception of the magnitude of their own equity, or wealth, invested in the property significantly affects the likelihood of default when the borrower is in financial distress. (Whitley, Windram and Cox, 2004; Hellebrandt, Kawar and Waldron, 2009; Lambrecht, Perraudin and Satchell, 1997; Figuera, Glen and Nellis, 2005 and Breedon and Joyce, 1992). This is supported in US based studies using loan-level data (see for example, Jackson and Kaserman, 1980). It is not clear, however, to what degree this phenomenon transfers to other countries as the limited recourse of lenders to borrowers' assets other than the property that is securing the loan is particular to numerous US states but practically unknown throughout Europe. In addition, some research argues that while household equity can play an important role in *increasing* the probability of default, it does not in itself cause default (May and Tudela, 2005).

The second theory which is found in the literature is based on the 'ability-to-pay'. Households that take on large amounts of debt relative to their disposable income should be more likely to face difficulties in making payments in the case of an adverse shock (e.g. interest rate rises, loss of income, unemployment etc.). A study on US cross-sectional loan level-data originated in 1969 (Jackson and Kaserman, 1980) however, finds that only the loan-to-value ratio was significant, while the interest rate variable (reflective potentially of debt-service) was insignificant. However, this finding may be less relevant for the UK case where a large proportion of loans are on variable rate. Most UK based studies seem to suggest that the debt-service ratio is a strong indicator of mortgage arrears (see for example, Brookes, Dicks and Pradhan, 2004; Whitley, Windram and Cox, 2004).

Most studies due to the way data are available, examine arrears rates as a proxy for repossession rates. However, the relationship between the two is not necessarily linear. The assumption made in many studies is that the characteristics of loans in arrears would not differ from the loans that are repossessed. There are, however, loans that do not transition from delinquency to repossession but cure. Being in arrears is often a temporary status and as argued by Ambrose, Buttimer and Capone (1997) has a value of delay, providing the borrower time to sort out financial problems and cure

[4] Lambrecht, Perraudin and Satchell (1997) suggest that the two theories are not distinct. This is because not only can short-run fluctuations in income influence default, but due to the fact that a default does not erase the debt to the lender, the level of equity a borrower has will also influence the default decision.

the loan. Some borrowers may sell the property and prepay the mortgage. An important determinant of this is whether the borrower has equity in the house and therefore stands to lose this equity if the property were repossessed. Households with negative equity because the property value (potentially due to house price declines) is lower than the mortgage loan are very likely to default. In contrast, households with significant equity may find a way out of the payment difficulties by either selling the properties or by withdrawing equity from the property and refinance with another lender. A necessary condition for this is that credit constraints do not limit the opportunity to refinance.

Survey research by Coles (1992) also sheds some light on drivers of arrears and repossession. Coles using a survey of UK lenders from December 1991, finds that arrears are mostly associated with unemployment or other income shocks. Moreover, those experiencing arrears were mostly either self-employed, working in the construction industry or else in a commission based business. The paper also finds that 60% of loans in six months or more arrears are still able to make a significant repayment i.e. they may not necessarily default. The survey also found that repossessions were instigated after about six months of being in arrears.

Our study focuses on both arrears and repossessions of loans. Given the different routes loans in arrears can take, we argue that some variables may have a stronger effect on repossession compared to arrears. This hypothesis is driven by the conjecture that different types of loans have a different tendency to roll on from arrears into repossession. For instance, lenders may be quick to repossess high loan-to-value loans which they do not expect will be able to refinance or cure. While we do not have sufficient data to directly test on roll rates of loans with various characteristics, we are able to draw conclusions from a comparison of risk factors between the arrears data and the repossession data available to us.

There is little research on the UK mortgage market that focuses on specific borrower characteristics as determinants of default. A few recent publications which focus on the US subprime market have highlighted the poor credit profile of borrowers and their low credit scores as one of the strongest drivers of default in the recent subprime crisis (see for example, Mayer, Pence and Shurland, 2009 and Demyanyk and Hemert, 2009). We expect that this phenomenon is prevalent also for the recent credit crisis in the UK. Borrowers who in the past had difficulties in managing their finances were able to obtain mortgages in the non-conforming sector. We expect that such individuals are more likely to fall into arrears or to be repossessed in the current downturn.

Similarly borrowers with volatile income streams should be more susceptible to economic cycles. In this respect we focus on borrower's employment status. Coles (1992) finds evidence that self employed borrowers are more likely to fall into arrears. Intuitively, borrowers who earn a fixed monthly salary and enjoy stronger protection from regulation are more likely to be able to continue with their monthly mortgage payments than self employed borrowers who generate income from their own business and are more dependent on the respective market conditions. Therefore self-employed borrowers should be more susceptible to economic cycles and interruption of their business.

A large extant of literature focusing on the US subprime crisis has examined whether specific product features were important drivers of default and delinquencies. The US literature shows that product characteristics had a relatively smaller impact on loan performance (Demyanyk and Hemert, 2009). Among the product characteristics, balloon mortgages had the highest probability of default, while fixed rate mortgages showed the best performance. This effect, as the authors argue, could be a self-selection bias, with the best borrowers selecting fixed rate mortgages. Interest-only loans in the UK operate similarly but not exactly like balloon mortgages in the US. [5] They are also common in both prime and non-conforming market taking up around approximately 30% and 50% respectively in each market sector. This has however, declined substantially during 2008.

The remainder of the paper is set out as follows: section 2 provides a broad overview of the UK mortgage market, its evolution since the early-1990s recession and recent developments; section 3 describes the data set and key summary statistics; section 4 presents univariate and multivariate analyses; section 5 summarises and concludes.

2 UK MARKET OVERVIEW

2.1 Historic Development

The UK mortgage market is one of the most sophisticated and competitive in Europe and is characterised by its prime, sub-prime and non-conforming sectors. Traditionally, residential mortgages in the UK were provided by building societies. However, following changes in legislation in the 1980s, banks, insurance companies and other lenders were able to enter the mortgage market. These new entrants introduced new mortgage products and expanded lending to market segments not catered for prior to the deregulation, which ultimately resulted in the diversity of borrower and product types known to current observers of the market.

The subprime market was established in the aftermath of the housing recession of 1990-93 which had the effect of creating a demand for mortgages among borrowers who had previously defaulted on a loan or had otherwise experienced financial problems and had adverse information on their credit record. during the last recession of the early 1990s, i.e. at a time when banks and building societies, had suffered substantial losses on their lending books, capacity and willingness to lend to such borrowers was limited. As a result, specialised lenders filled the void and launched the subprime market by offering loans to borrowers with adverse credit history. They originated mortgages through intermediaries rather than branch networks and funded themselves by wholesale debt usually borrowed from investment banks rather than by retail deposits.

The companies that pioneered the development of the subprime market in the early 1990s have also been pivotal in innovating other products in the UK mortgage market, such as loans for self employed applicants, temporary contractors who could self-certify their income, and also employed borrowers who may have more than one job

[5] Such loans are characterised by a bullet capital payment at maturity of the mortgage, with only interest payments being made through the life of the mortgage.

or source of income. They have also been instrumental in developing the buy-to-let (BTL) market, where the borrower's ability to repay the loans was measured on the basis of future rent rather than their own income. By the early 2000s these types together with the subprime segment were collectively known as non-conforming.[6]

As competition around subprime lending grew specialised lenders who initially started off by catering for subprime borrowers expanded their range to offer loans to borrowers with only limited adverse credit (also known as 'near prime'). At the same time prime lenders, in search for higher yields, also broadened the range of borrowers they would accept and also started to issue loans with limited adverse credit information.

This expansion of the UK mortgage market, in combination with the increased number of participants, intensified competition, which, prior to August 2007, was a fundamental driver behind the general relaxation of underwriting criteria employed by lenders specifically within the non-conforming sector.

2.2 Underwriting Standards

In the prime sector mortgages are typically underwritten using credit scoring models developed individually by each lender. The features that each lender considers when building a scorecard differ from lender to lender. Generally however, prime lenders' score cards will take into account the explicit credit history of an applicant as well as factors that behaviourally are felt to contribute to a higher or lower likelihood of default. Credit features that would typically be considered include the amount of County Court Judgments (CCJ), Bankruptcy Orders (BO) Individual Voluntary Arrangements (IVA) and prior mortgage arrears as well as payment history of unsecured lending (such as personal loans/credit cards and hire purchase agreements). Behavioural characteristics that would generally be considered include whether the borrower is on the electoral register, the applicant's age, and the age gap between the two applicants if the applicant is a joint applicant. Typically, lenders in the prime market would not allow BOs/IVAs, significant CCJs or prior mortgage arrears, and performance on payments on other lending would be factored into the scorecard. Indications of poor past performance would lead to a lower score and therefore increase the likelihood of a decline decision.

The vast majority of UK subprime mortgages were not underwritten using credit scoring models. Instead, loans were either manually underwritten or, where automation was used, it was rather deployed to assign a loan application to a particular product type. This level of automation did not attempt to look at other personal details of the applicant, for example whether the borrower is on the electoral register. Generally, where credit scoring was used in subprime it was used as a tool to dictate the level of scrutiny an application will receive at the manual underwriting stage, it was not used to make the decision.

[6] Non-conforming products include loans to subprime borrowers (borrowers with materially adverse credit history), second charge loans, loans for which borrowers self certified their income; loans secured on BTL; right-to-buy and lifetime or equity release loans.

2.3 Current Crisis

The UK mortgage market has undergone significant changes due to the unprecedented liquidity crisis which broke in August 2007, following increasing concerns over the performance of US sub-prime mortgages. The subsequent disruptions to the global financial markets caused all lenders to substantially revise their mortgage origination practices.

The liquidity problems of banks and the general change in global investor appetite forced large parts of the non-conforming sector to stop lending. The prime market continued issuance of loans, albeit at much tighter lending criteria and at higher margins over the refinancing rate. In terms of underwriting criteria, the most prevalent reaction has been the reduction of LTV ratios lenders are prepared to lend against.

This tightening of lending criteria has been viewed as positive for performance of future originations, but this unprecedented disruption to the mortgage market has the side effect of causing defaults of existing borrowers on riskier products. This is in marked contrast to the situation during 2004 to 2007 where strong house price appreciation and an easy availability of credit meant that even those borrowers with severe credit problems or those on riskier mortgage products would have had no difficulty in refinancing once their discount period ended to lock in a cheaper 'teaser' rate. Past data on severe delinquencies and defaults analysed by Fitch Ratings indicates that the majority of subprime borrowers who fell behind in their payments had been able to remortgage their way out of problems by withdrawing additional equity from their house. With a tightening of the mortgage market and the significant contraction in house prices, many borrowers found themselves unable to do so and defaulted on their mortgage.

A distinct characteristic of the recent UK market is the significant growth in residential mortgages solely underwritten on the rental income of the property, rather than the borrower income. Such mortgages have been termed 'buy-to-let' loans and have been growing in popularity since their inception in 1996 up until the onset of the credit crisis in Q4 2007 where they constituted 13% of all gross mortgage advances. The buy-to-let sector enjoyed stronger growth during the boom phase and, like all non-conforming products, suffered a sharper decline in volumes than the prime conforming sector. Prior to the crisis market observers were divided over whether buy-to-let mortgages constitute higher or lower risk than owner-occupier mortgages. Buy-to-let investors tend to be older and more financially savvy, with a long-term investment aim in mind. On the other hand, property investors also tended to exhibit higher debt leverage and are exposed to the fate of the rental sector. We do not share the popular view that buy-to-let investors are hedged against house price declines which is based on the theory that, during a downturn, the population turns demand towards renting rather than owning as long as house prices are decreasing, because this is based on the questionable assumption that housing demand does not decrease as a whole during a downturn. Rather, we expect buy-to-let mortgages to perform in parallel to the business cycle, i.e. lower default probability than owner-occupiers in an economically benign environment and worse in a downturn.

3 DATA AND SUMMARY STATISTICS

We collected a unique dataset on over 500,000 mortgage loans drawn from UK residential mortgage backed securities (RMBS) rated by Fitch Ratings. Most of our dataset relates to originations between 2004 and 2007. For comparison, all mortgage loan advances in the UK over the same period amounted to close to GBP10 million; this is combining remortgages and house purchases as well as the prime and the non-conforming sector.

The data set includes information on loan and borrower characteristics from the time of origination. In addition, we have the latest performance information on the loan, i.e. its worst arrears status since origination until March 2009, the time of default or the time of prepayment.

The available mortgage pools contain originations since 2000 by a variety of UK lenders in the prime and non-conforming sectors. The data are representative of the overall market, as they cover a wide spectrum of loans ranging from prime to non-conforming lenders. For non-conforming loans, we have two separate datasets, first where performance information was recorded in terms of repossessions ('repossessions information') and second where performance information was recorded in terms of number of months in arrears ('arrears information'). We report summary statistics and analyses for each dataset separately.

3.1 Coverage of Dataset

Table 1 A & B show the number of loans in the dataset by transaction for non-conforming and prime, respectively. Each loan defines one performance observation, i.e. repossession or worst arrears status. Transactions by the same originator are subsumed under a single name, typically the name of the originator or the securitisation programme. For example, there are several Bluestone transactions included, which we report as a single dataset for Bluestone transaction series as in Table 2. We received arrears information on loan level data on four master trust transactions[7] backed by prime mortgages as shown in Table 1B.

The data cover loans originated since 2000 (see Table 3). The bulk of the observations stem from originations between 2004 and 2007. The concentration by vintage is particularly strong for the non-conforming sector which experienced large growth during this period. On the prime side, the distribution of loans is more spread out by origination vintage.

Most of the repossession information comes from loans that were repossessed in 2007 and 2008 (see Table 4).

[7] Master Trusts are structured transactions which allow for continuous revolution of the underlying pool and periodic issuance of additional notes. Most UK RMBS and Consumer ABS Master Trusts are maintained by large commercial banks or building societies and contain several hundered thousands of loans.

3.2 Biases, Imperfections and Solutions

Due to the differing reporting standards and internal standards among lenders we were faced with the challenge of dealing with partly incomplete data. For the sake of clarity we refrained from imputing missing data and preferred to base univariate and multivariate analyses on as many available observations as possible. This means that analyses including risk factors that are not populated for all observations are limited to the subset of observations on which all risk factors are available.

Note that the selection of loans according to eligibility criteria for the securitisation and the self-selection of securitising banks may lead to biases not visible to us compared to typical mortgage pools held by banks. In particular, our study does not attempt to identify drivers of early delinquencies since securitised loans typically have seasoned at least a few months before being included into a transaction. The provisions of a securitisation normally include restrictions as to their arrears status. Hence, early delinquencies are typically excluded from securitisations and are not captured in the data available to us.

Whilst being one of the most comprehensive datasets compiled on the UK mortgage market the data exhibit a few imperfections which we will address during the analysis:

(1) We lack adequate performance data on buy-to-let loans originated by prime lenders. Therefore, any conclusions drawn on buy-to-let loans are representative of the non-conforming sector only.
(2) We lack data on repossessions for prime loans, therefore a comparison between drivers of repossessions vis-à-vis arrears is restricted to the non-conforming sector.
(3) For three transactions we have only been provided with repossession data and for five transactions only the arrears status. We will separate analysis on different performance indicators and draw conclusions on the difference in section 4.2.1.
(4) There are a small percentage of non-conforming loans for which we were provided with both repossession and arrears information. The limited conclusions that can be drawn from this dataset are reported in section 4.2.1.
(5) Due to the different mix of originators in the dataset, some of the results are bound to be driven by differences in underwriting. We try to control for these effects in the multivariate analysis via dummy variables. However, such technical correction does not capture more delicate bias such as resulting from occasional changes to underwriting practices of one lender over time.

As evident from the above, we separately study performance according to two different measures of default, based on availability of the performance measure.

First, we use a proxy default measure for loans that have ever been in arrears for more than three months in their life (henceforth referred to as 90ever). Arrears are broadly defined as the shortfall on scheduled payments past one month. This measure has several advantages. It serves as a leading indicator of the default event, which is typically referred to as unlikely to pay. This measure allows us to capture the risk of a loan at an early stage as enforcement proceedings are typically at a later stage and depend on the speed with which lenders decide to foreclose the property. This way we can capture loans from recent origination vintages which have yet to be repossessed but have already fallen into arrears.

Second, we use information on actual repossessions. This measure is more closely related to the enforcement stage and ignores loans that cure, i.e. loans that repay the overdue amounts, resume continued payment and can thus be treated as performing loans again, and loans that prepay prior to the property being repossessed. Due to the late stage at which repossessions are recorded fewer observations are available under this default definition. However, as our data set covers performance information from the economic downturn in the UK, sufficient observations are available to form a number of conclusions. The use of the two default definitions combined also allows us to test whether the drivers of repossessions are the same as the drivers of 90ever status.

Information on both arrears and repossessions are available up until March 2009. As arrears and repossessions have only begun to rise since Q3 2007 the data only captures the first part of an economic downturn. Default drivers may evolve over time and different risk factors may become prevalent during a later stage of a downturn environment.

Figure 1 summarises the default rates: percentage of loans repossessed ('repossession rate') and percentage of loans that were in 90ever ('arrears rate') by origination vintage. There are a reasonable number of repossessions and arrears in the dataset for model estimation purposes. As older vintages have had more time to go into repossession or arrears, we naturally see higher default rates as compared to more recent vintages such as 2007. It is worth noting that some of the differences are also transaction specific. For example, for the prime data the different vintages also have a different mix of transactions with different loan-to-values and debt-to-income ratios which may also be driving the results. This will be controlled for in the multivariate analysis. [8]

3.3 Descriptive Statistics on Key Risk Factors

Before turning to the univariate analysis of default rate we analyse the distribution and historical development of those risk factors identified in the literature and in our analysis. [9]

3.3.1 Original Loan-to-Value Ratio (OLTV)

The literature usually associates the OLTV with the willingness to pay since the leverage of the borrower indicates the degree of commitment to the investment. Between 2005 and 2007, UK lenders relaxed underwriting criteria to allow for increasingly high-OLTV loans (i.e. loans with particularly little equity by the borrower). This is evident also in our dataset with average OLTVs having increased

[8] The 90-ever rate for 2000-2002 vintage in non-conforming are very high, but resulted in very little repossessions. The number of loans here are very few and skewing the results.

[9] Please note that summary statistics are not reported from this point hereafter where vintage information was missing.

between 2000 and 2007 from around 70% to above 80% in the non-conforming sector and from around 62% to 70% in the prime sector.[10] Figure 2-4 show the distribution of OLTVs for prime and non-conforming loans, where it is quite evident that a higher proportion of loans were originated in the high OLTV bands in recent vintages. However, some of these high concentrations are driven by specific lenders rather than the overall trend.

3.3.2 Debt-to-income ratio (DTI)

A borrower's ability to meet the monthly mortgage payment is dictated by the relationship between their income and the monthly payment. There are two widely used measures for the perceived affordability of a loan: the income multiple (IM) and the debt-to-income ratio (DTI). The IM simply expresses the size of the loan advance as a multiple of the borrower's annual gross income.[11] However, mortgage lenders in the UK are maintaining this measure only for provisional indications and have gradually moved towards DTI type measures to assess a borrower's affordability. The DTI is viewed as a more precise measure of affordability since it takes into account the debt payments and net income. Lenders vary in their definition of the DTI ratio. For instance, monthly debt service payment may include or exclude liabilities other than the mortgage and income may be adjusted to reflect additional earnings and regular expenses. Based on the dataset we define DTI as the monthly debt service payment on the mortgage as a proportion of the adjusted monthly net income (net of taxes and national insurance contributions). Average DTI has also shown small increases over time as evident in Table 6. Figure 5-7 show the magnitude of impact more clearly whereby a much larger proportion of loans were originated in the higher DTI bands in recent vintages, especially in the case of prime.

3.3.3 Loan and Borrower Characteristics

Table 7-8 summarise key borrower and loan characteristics in our dataset. While we considered several more borrower and loan characteristics, those reported in this summary table are the ones that turned out significant in one of the logistic regressions.

As might be expected, non-standard loan features are less prevalent among prime loans compared to non-conforming loans. Similarly, interest only loans are also far fewer among prime compared to non-conforming loans. Interest-only loans have been a fairly stable percentage of mortgage loans advanced in both prime and non-conforming. However, more recent vintages of 2008 and 2009 are showing a drop in interest-only mortgages. Such loans implicitly rely on the ability of the borrower to manage the build-up of capital for the repayment of the loan at maturity or to successfully find a refinancing opportunity. In the buy-to-let sector, interest-only loans are the predominant form of repayment type due to tax reasons. Fast-track loans make up only 17% of all prime originations which indicates that the reliance on stated income was used by lenders sparsely, while the opportunity for borrowers to self-

[10] Weighted average LTVs are higher by 3-5% but the overall trends are preserved. We don't report weighted average LTVs because the multivariate regressions are numbers based and weight each observation equally.
[11] For example, a borrower with a loan of GBP 150,000 and an annual gross income of GBP 50,000 has an income multiple of three.

certify their income was a very popular product within non-conforming lending. The much larger percentage of remortgage loans among non-conforming lending (around 60-65% of lending versus approx. 40% in prime) can be explained by the fact that some non-conforming lenders were specifically targeting borrowers in payment difficulties for this product, while remortgaging among prime lenders was mainly the result of a borrower seeking for a better interest rate.

For non-conforming loans we also analysed additional available information on adverse credit characteristics of borrowers. Less than half of the borrowers in the non-conforming datasets have adverse credit as per our definition. We have created an adverse credit flag which is defined as loans which have had a prior bankruptcy or an individual voluntary arrangement (IVA) or mortgage arrears 6 months ago or mortgage arrears 7-12 months ago or a county court judgement (CCJ). Therefore, adverse credit subsumes all the other categories that are listed in Table 8. Other borrowers in the dataset may have some adverse credit history that is not being captured by the four variables described in Table 8.

There is a sizeable proportion of borrowers who are charged with a CCJ over the past twelve months prior to loan origination. In the UK a CCJ is issued by the court when an individual has failed to make contractual payment on unsecured debt (for example, a credit card liability). We use information on the number and amounts of all CCJ to test for their impact on default probability. The percentage of loans with any number of CCJs ranges between 17-28% in the two datasets. Of these, while a large percent of loans with CCJs have a record of only one CCJ, there is still a sizeable number with more than one CCJ (approximately, 30-50%). The typical (median) amount of CCJ charges for any one borrower is at around GBP1000, while the average is at around GBP4000. In this case the average is skewed upwards due to very large accumulated CCJ charges for some borrowers which can go up to a maximum amount of close to GBP1 million. We also had information on the time elapsed since the last CCJ recording. However, the poor quality of this data prevented us from drawing any meaningful conclusions.

4 UNIVARIATE AND MULTIVARIATE ANALYSIS

This section presents results from univariate and multivariate regression analyses using the default indicators and loan and borrower characteristics as introduced in section 3.

4.1 Univariate Analysis

These analyses help to gauge the potential predictive power of single risk factors and prepare the multivariate analyses presented in section 4.2.

4.1.1 Original Loan-to-Value Ratio

Borrowers with a higher amount of equity in their property (as represented by a low OLTV ratio) tend to be less often in arrears and repossession proceedings. Figure 8-10 show a positively increasing relationship between OLTV and default for all vintages under study. For non-conforming loans we only report the three most recent vintages where the dataset is sufficiently well populated. We included all vintages with more than 3,000 loans.[12] The non-conforming data show a reduction of arrears and default rates at the highest OLTV bands, i.e. above 80% OLTV for arrears and above 90% OLTV for repossessions. It is likely that stricter underwriting procedures applied at the high LTV bands are responsible for this relationship, such that low-equity mortgages are approved only if the credit risk profile of the loan is low otherwise.

Notice also that the worst overall arrears and repossession rates are recorded neither for the oldest nor for the most recent vintages, but for intermediate ones. The older vintages are less affected by the current downturn due to prepayments and substantial house price appreciation that has occurred since origination. The more recent vintages did not have time to build up the level of arrears and repossessions of the older vintages. The 2007 vintage, however, is expected to ultimately perform similar or worse than the 2005 and 2006 vintages.

We note that the influence of OLTV is much stronger for repossessions than it is for 90ever rates. This phenomenon points towards repossession proceedings being started earlier the less equity the borrower has in the property. We investigate this topic in more detail in section 4.2.

4.1.2 Debt-to-Income Ratio

Borrowers who are making larger mortgage payments as a proportion of their disposable income have higher default rates in both prime and non-conforming sectors. We do find again a flattening of default rates towards the highest DTI buckets in Figure 11-13. Similar to the discussion of OLTVs, this is likely to be related to stricter underwriting procedures in the high risk segments. Note also that the flattening starts at lower levels for prime mortgages (from around 30% DTI) compared to non-conforming mortgages (from around 40% DTI).

4.1.3 Borrower and Loan Characteristics

Table 9-11 summarise the relationship between the default rate and various borrower and loan characteristics. The statistically significant t-tests suggest that there are clear differences in default rates across many loan and borrower characteristics. For the continuous variables such as OLTV and DTI, we computed the Johnkheere-Terpstra test, which is a nonparametric test for ordered differences among classes. We distributed the OLTV and DTI in various bands and tested the null hypothesis that the distribution of the default rate does not differ among the classes. The test rejects the null hypothesis of no-trend among the OLTV and DTI classes.

It should be kept in mind that univariate analyses do not fully capture relevant multivariate relationships. For example, buy to let loans here appear to have lower default rates compared to owner-occupied loans. This is due to the lack of control over other characteristics such as OLTV, DTI and other loan features. There are also vintage specific differences that are not captured in the analyses in this section. The

[12] While this threshold may appear arbitrary the model fit with fewer observations posed problems and the maximum likelihood estimation was not converging.

regression analysis reported in section 4.2 sheds more light on these more complex relationships.

4.2 Multivariate Analysis

Methodological Remarks

We estimate the following logistic model to predict the factors driving probability of default of a mortgage loan.

$$\Pr(\text{Default}) = 1/(1+e^{-bx}) \quad (1)$$

Whereby b is the vector of coefficients to be estimated and x is the vector of risk factors, i.e. borrower characteristics, loan characteristics and control variables such as dummy variables for the originators. The disturbance term follows a logistic distribution with a fixed variance.

We perform regression analyses on both the indicator for having ever been 90 days or more in arrears and the indicator for repossession. All key variables listed in section 3.3 were used in a series of regressions, taking into account the limited availability of some factors for certain transactions.

In addition, originator specific effects are introduced to control for differences in underwriting procedures across lenders. These qualitative differences can have a significant impact on the probability of default. Since originators may have sponsored several transactions with different collateral over time, we also introduce transaction specific dummies. This is especially important as transactions may contain different eligibility criteria.

We test for the stability of the model with respect to different origination vintages and repossession periods. This way effects from changes in underwriting procedures, marketing, distribution channels or economic environment are tested more thoroughly. For example, the 2006 and 2007 vintages were originated at a time of fierce competition among lenders and may be expected to have resulted in the origination of riskier mortgage loans, all other characteristics of the loans being equal. Controlling by origination vintage allows to take into account any such time-specific effects.

Interaction effects were also introduced to determine any risk-layering in different product and borrower types. We tested on a number of interactions, including various combinations between high OLTVs, self-certified, self-employed, adverse credit, remortgaging and interest-only loans.

4.2.1 Results

The regression results are summarised in Table 12-17. Separate estimations are performed for prime and non-conforming loans and within non-conforming separate analyses using the repossession indicator and the 90ever arrears indicator as the dependent variable. We report results for the entire dataset and separately for only those vintages with a sufficiently large number of observations, i.e. for non-conforming origination years 2005 to 2007 and for prime origination vintages 2004 to 2007. We considered various borrower, product and loan characteristics for the regression analysis based on a priori expectations. Care was taken not to introduce correlated variables, for example flats (property type) and new builds. Some variables were only available for specific pools and regressions were carried out separately. [13]

We report marginal effects instead of coefficients for the exogenous variables to facilitate evaluation of whether their magnitudes are of economic importance. Marginal effect for a variable *i* is calculated as follows:

$$Marginal_i = F\,(b'X + b_i s_i) - F\,(b'X) \qquad (2)$$

In most cases, our key exogenous variables of interest are dummy variables such as product type (interest-only) or borrower type (e.g. self employed) that take on the values 0 or 1. For each of these variables, the reported marginal effect is the difference in predicted value for the dependent variable for a dummy value of 1 versus 0 (i.e. $s_i = 1$), with all continuous exogenous variables evaluated at their means and categorical exogenous variables evaluated at their mode. For the continuous exogenous variables of OLTV and DTI, the reported marginal effects are difference in the predicted value for the dependent variable for a 10% increase from the mean value (i.e. $s_i = 10\%$). For the continuous variable of stabilised margin, we report the marginal effect of a 1% increase in stabilised margin. We also report in the regression outputs $F\,(b'X)$ as the 'base' probability of repossession/arrears where the continuous variables are evaluated at their means and the dummy variables at zero. This facilitates a comparison of the marginal effects also in relative terms compared to the base probability.

The selection of the model was based on a combined consideration of several measures of goodness of fit, including log likelihood, Bayesian information criterion (BIC), Akaike information criterion (AIC), Somer's D, pseudo r-squared and residual analysis in choosing the final model.[14] We also carried out residual analysis for several sub-groups to see if the model fit is poor for specific segments in section 4.2.2. Coefficients that were insignificant in the model have not been reported in the results.[15]

Most drivers of default for prime are also relevant for non-conforming

The regression results suggest that aside from adverse credit information (such as CCJ, bankruptcy orders, IVAs or prior arrears) which are characterising the subprime segment, we find very similar drivers of default in both sectors. High-OLTV loans, interest-only loans and remortgages are defaulting significantly more often than average for both prime and non-conforming.

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[13] In addition to the variables in the final model, we analysed property type, region and the type of interest charged on the mortgage.

[14] When analyzing data with a logistic regression, an equivalent statistic to R-squared does not exist. The model estimates from a logistic regression are maximum likelihood estimates arrived at through an iterative process. They are not calculated to minimize variance, so the OLS approach to goodness-of-fit does not apply. However, to evaluate the goodness-of-fit of logistic models, we use pseudo R-squared as reported by SAS which is based on log-likelihood.

[15] We used backward selection to remove variables that are not statistically significant at or below the 10% significance level.

We find that the larger loan-level impact of OLTV on arrears and repossessions compared to the DTI ratio holds for both non-conforming and prime loans. [16] This is in contrast to the study by May and Tudela (2005) who find the OLTV not to be a statistically significant driver of household payment problems. Several explanations allow to rationalise this phenomenon: Firstly, borrowers may consider the costs and benefits from continuing payment. If they have little equity, they will have less incentive to continue payments and may choose to default. Based on the 2004-2007 vintages, the fact that income was (or was not) sufficient to meet the mortgage payments was of less importance, due to the fact that high house-price appreciation allowed borrowers to refinance to a larger debt amount.

A second and more plausible explanation is the impact of an 'underwriting effect' over time. This effect is clearly visible in the negative influence of high DTIs on prime arrears, i.e. prime loans with a higher DTI are less likely to default.[17] It appears that prime lenders apply strong restrictions on affordability in the underwriting process such that loans with the worst affordability measure tend to perform better than average as evidenced in the consistent negative coefficient across vintages. An example of this may be that loans with high DTIs are only approved to known private banking clients who have sufficient other assets and a strong payment history with the originator. We are unable to ascertain whether this hypothesis is true due to lack of data on the borrowers' general financial position and their relationship with the mortgage originator.

Drivers of repossessions are similar to drivers of arrears

For non-conforming loans we are able to compare the results of 90ever arrears with the results from repossessions (see Table 14-15).

We find that the same borrower and loan characteristics that influence arrears are also important in influencing repossessions. While to our knowledge there is no public UK study that compares the two, our results are in line with findings from the US reported by Demyanyk and Hemert (2009). They do not see any significant difference between their delinquency and foreclosure regressions.

Two additional product features in the non-conforming market, however, appear to be significant drivers for repossessions, but not for arrears: loans made under the right-to-buy (RTB) scheme and buy-to-let loans (BTL). While RTB and BTL loans do not necessarily have higher arrears compared to non-RTB and owner occupied, respectively, the roll rate for these loans into repossession is much higher. For BTL loans this means that among two borrowers who have been unable to manage their personal finances in the past those who are then trying to engage as property investors

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[16] We also tested whether the predictive power of DTI as a measure of affordability is mainly due to it incorporating the size of the interest rate charged on the loan in the numerator. We find the evidence to be mixed (see for prime regression results including stabilised margin). In most cases, when we include the stabilised margin over the Bank of England base rate into the regression, the DTI continues to be significant. The statistical significance of the stabilised margin itself is variable.

[17] This is similar to the graphical analysis in Figure 7 which shows this effect.

are less likely to prevent repossession compared to those who purchased the house they are living in. BTL loans, which were found to be insignificant in the non-conforming arrears regression model, are positively significant for the repossession model. The negative coefficient for 2007 BTL loans is suggesting that these loans are performing better than owner-occupied loans. However, this may again be related to the fact that we do not have enough performance history for 2007 originations to fully determine the effects of BTL.

The results on RTB are likely to reflect the functioning of the scheme. Council tenants have the opportunity to purchase their own homes through the UK government's scheme. This gives tenants the right of first refusal to purchase the home that they are renting from their local authority at a discount to the effective open market value. Should the property be re-sold within 5 years, the purchaser is liable to repay a portion of the discount, relative to the length of time since the property that was bought. Seasoned RTB loans of more than 5 years hence benefit from the discount on the property value which allows them to sell the property and repay all outstanding liabilities. More recent originations, however, do not have this option since they are still exposed to the liability against the local authority. Given the house price decline over the last years, it is thus likely that those borrowers are less likely to recoup all their liabilities from selling the property. Given also that borrowers in that scheme tend to be lower skilled, low-income earners, lenders are likely to see less chance of cure and start the repossession process earlier than usual. Moreover, the best houses were bought early on when the scheme was first introduced nearly 20 years ago. Arguably what is left and more importantly what is reflected in our dataset, are a portion of the least desirable housing stock. This might make selling the house to clear arrears higher as there may be a larger forced sale discount for this type of property.[18]

Some variables have a different effect on likelihood of repossession than arrears

In terms of economic magnitude of the drivers, we notice a slightly stronger influence of OLTV in the regression on repossessions, particularly the 2006 vintage. While the marginal effect for the 2005 vintage is stronger for 90ever, we are careful not to over-interpret this marginal effect as relative to a 'base' probability of arrears of 23.8% for the 2005 vintage, the marginal effect on a relative basis is smaller. Moreover, the 2005 vintage also has a small number of observations and poor model fit.[19] We find a stronger impact of equity on the likelihood of repossession relative to the likelihood of long-term arrears. The results show that not only are high-OLTV loans (i.e. little equity in the property) more likely to fall into arrears compared to lower OLTV loans, once they are in arrears they are also more likely to be repossessed. This may be explained with the limited prospects of curing (potentially refinancing into a higher LTV product or via selling the property and prepaying the loan without default) that lenders see in loans that have fallen into significant negative equity that has built up due to the drop in house prices since origination.

[18] Note that these results only relate to non-prime lending. Our database does not contain RTB and BTL loans in the prime sector so that no comparison between the two sectors can be performed.

[19] The goodness of fit measures: The AIC was lower than for other vintages and the Hosmer-Lemeshow test was statistically significant at 10% level.

We find a less strong impact of DTI overall on both the likelihood of arrears and the likelihood of repossession. The impact of DTI is much weaker for the repossession regressions. In fact, it is insignificant except for the 2006 origination vintage.

These findings contrast somewhat with the US study by Demyanyk and Hemert (2009) who also report results in terms of marginal effects. Their paper finds that marginal effects are consistently higher across all borrower and product characteristics for the probability of falling into arrears versus the probability of repossession.

To ensure that the results were not influenced by the slightly different pools of loans which were used for the arrears and the repossession analysis, we analysed the effects on a reduced dataset among only those loans for which both 90ever arrears and repossession observations were available. This sample consists of approximately 22,000 loans in total from various vintages (comprising of 842 repossessions and 3,295 loans in arrears). In order to keep a critical mass of observations we did not separate vintages and estimated a single regression. The results (in Table 16) broadly match with those found for the broader sample. The only exceptions are BTL and RTB which cannot be included in the reduced sample because it does not contain any BTL and RTB loans.

Adverse borrower features are the most significant relative to other borrower or product features

The indicator for adverse credit history for a borrower is highly significant for both arrears and repossessions among non-conforming loans. In addition to OLTV and DTI, it seems to be the single most important factor that explains default behaviour in loans. Adverse credit borrowers have a higher probability of repossession in the range of an additional 5%-13%, with the impact similar for the 90ever regression keeping in consideration the higher 'base' probability of arrears (9%-24%) relative to the 'base' probability of repossession (0.3%-6%).

Other borrower characteristics that are significant are self-employment and remortgaging. We were unable to include self-employment as an explanatory variable into the regressions on repossessions, as the number of observations for which this information was available was very low.

Self-certification products that allow borrowers to certify their own income also carry the risk of fraud as has prominently been the case in the US subprime sector with the so-called 'liar loans'. [20] We find a similar effect whereby loans where the borrowers self-certify their income have a higher probability of default all else being equal. The marginal effect however is much larger ranging between 0.2%-2% for our study, as compared to the US study by Demyanyk and Hemert (2009) who find a marginal effect between 0.25%-0.68% for low documentation loans. However, these are only absolute effects; we are unable to compare the effect in relative terms between the two studies due to the US study not reporting the 'base' probability of default. While the UK products have had a lower maximum LTV limit than the US, the results suggest

[20] In the non-conforming sector, borrowers were able to choose not to have their incomes verified. The lenders performed only varying degrees of due diligence, with some insisting on an accountant's letter for self-employed borrowers and others making contact with the employer to confirm employment of the applicant, though income was not discussed.

that after controlling for this LTV limit, the products in the UK have been relatively more risky than the no (or low documentation) products in the US. We also found some evidence of risk layering, where other borrower and loan characteristics when combined with an impaired credit history leads to a further increase in the likelihood of default. We find the effect of self-certification and adverse credit history combined was larger than the cumulation of the two separate effects. The magnitude of the interaction effect is relatively small of about 1-1.5%, but statistically significant.

In the conforming sector, there is no explicit self-certification product. Instead, some loans undergo a leaner review process (so-called 'fast-track') based on the lenders choosing, typically if the LTV is within a maximum limit and the borrower's credit score is not exceeding a certain threshold. The regression results show that these 'fast-track' products behave differently from 'self-certification'. They also appear not to be comparable to low documentation loans in the US prime sector. Standards for the relaxation of income-verification tended to be more stringent among prime lenders in the UK. Our evidence shows that UK fast-track loans have a lower probability of default compared to fully income verified loans, though the economic magnitude is small.

Interest-only loans are 0.8%-2% more likely to default than the 'base' probability of default. The effect on a relative basis varies across prime and non-conforming regressions but is in the order of between 7%-30%. Interest-only loans could pose two potential risks: (i) that the borrower is unable to make the interest payment upon maturity. Typically (though not generally monitored by lenders), borrowers build up an investment pool to make the bullet payment of the principal at the end of the term of the loan. However, there can be a risk of shortfall at maturity as the nominal value of the funds at maturity may be smaller than the outstanding balance on the loan; and (ii), that borrowers only select interest-only mortgages due to affordability constraints as they are unable to make payments for both capital and interest from their regular income. Note that the regression analysis only picks up the latter effect. This is because the data set does not span a long enough time to allow for observations of interest-only loans that have reached maturity.

We also analysed second charge loans. While second charge mortgages were commonly available in the non-conforming sector, these loans only appear in our dataset in few of the transactions. For the 2006 vintage where the data were reasonably well populated we find second charge loans to be more likely to fall into arrears, but less likely to be repossessed as compared to first charge loans. We believe this effect is only a short-term anomaly related to different timing of repossessions between first-charge and second charge loans. Usually second charge loans take longer to be foreclosed, as the second charge holder must jointly work with the first charge holder in the foreclosure proceedings. Moreover, given that the loss severities on second charge loans easily amounts to 100%, it may be likely that lenders are not seeking to foreclose these properties immediately and first focus on repossessions on loans where substantial recoveries are more likely.

Remortgaging shows relationship with default likelihood, but debt consolidation may be underlying driver

An active market for mortgage refinancing is common for both the UK and the US. Frequent remortgaging is the result of strong competition between lenders, low transaction costs (e.g. for stamp duties, estate agents, registration fees, prepayment penalties) and the lack of relationship banking. In an active refinancing market borrowers try to obtain a better interest rate or to extract equity from their property. The former is particularly prevalent where mortgages are taken out on teaser (or discount) rates. After the end of the discounted period, most borrowers 'shop-around' for a better rate. Extraction of equity can be done for various reasons, such as for investment in goods, but can also be related to financial difficulties of the borrower, as he or she tries to consolidate debt from other accounts. Cash-refinance has been found to be strongly related to delinquency and repossession in the US (Demyanyk and Hemert, 2009).

Similar to Demyanyk and Hemert's (2009) finding on cash-refinance, our regressions show loans for remortgaging turn out to be significantly more risky than loans extended for property purchase. It may be counterintuitive that remortgage borrowers appear to have a greater probability of default as many are only shopping for a better rate. We explored this in more detail and found that the significant coefficient is actually functioning not only as an indicator for ordinary remortgaging but also as a proxy for debt consolidation. Borrowers may withdraw equity from their home to consolidate (and repay) debts that they have built up. But since debt consolidation is rarely recorded as the motivation for remortgaging we are unable to clearly distinguish between debt consolidation and standard remortgaging. To carry out this check we re-estimated the non-conforming regression for the sub-pool where we had information on debt consolidation.[21] Due to the small number of observations we estimated the regression using the entire dataset rather than separating between origination vintages. The results are overall inconclusive. On the repossession data we find a strong positive relationship between debt consolidation and probability of repossession, and remortgaging is no longer significant (Table 17). However, for the arrears regression the opposite can be found, i.e. the remortgage variable continues to be significant and debt consolidation is insignificant. [22]

For prime loans, we did not have information available on remortgage for all transactions under analysis.[23] A separate analysis using fewer transactions supports the finding that remortgage loans have a higher probability of default. However, we do not have data on debt consolidation to verify the ultimate drivers of this effect (see Table 13).

Finally, we do not find first time buyers to have significantly different probabilities of default when all other factors have been controlled for. For example, for first time buyers, their relatively higher OLTV could be capturing any differences in default probability.

Trends over time mostly mild and as expected

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[21] This sub-pool comprises of Bluestone 061, Bluestone 071 and Leek 21.

[22] We also find some evidence of risk-layering between remortgagors and adverse credit history. While this coefficient was not robust across all vintages, it does suggest that remortgaging may have been used during these periods of house price rises (by all borrowers, but particularly adverse credit borrowers) to refinance out of financial difficulties.

[23] This sub-pool excludes Granite only from the transactions listed earlier.

Some factors can be expected to be more relevant during economic distress than others. For this purpose regressions have been performed on annual origination vintages. Since the dataset spans only the origination vintages 2004 to 2007 for prime and 2005 to 2007 for non-conforming and default observations up until March 2009 results on trends only refer to the time of the run-up to and the first part of the recent credit crisis.

The regressions on prime loans confirm that self-employed borrowers are more vulnerable to economic decline than employees as their income is more directly related to the economic environment. The coefficient has continuously grown for each vintage up until 2007 from a marginal effect of 0.2% to 0.5%. While, the 'base' probability of arrears has also increased during this period, this effect is roughly constant if measured on a relative basis to the 'base' probability of arrears. The opposite observation can be made with interest-only loans for prime as its impact has declined from a marginal effect of 0.42% for the 2004 vintage to 0.14% for the 2007 vintage.

The most striking trend can be observed with respect to new build properties. Loans secured on new build properties appear significantly more risky than loans on older properties. This is visible, however, only for the 2006 and 2007 vintages; the latter only for 90ever arrears. The results indicate – as was recognised in the aftermath – that misincentives for this product were not prevalent during 2005 but grew tremendously in the subsequent years. We test additionally whether the riskiness of new build properties can be explained by incorrect valuations, since in addition to deposits and other incentives being provided by builders on new build properties, there was a systematic overvaluation of these properties. By implementing a reduction of the property value of 10% by way of raising the OLTV on new build properties, we find that the new build coefficient becomes insignificant.

4.2.2 Residual Analysis

We use Pearson residuals which are a component of the chi-squared statistic to identify if there are specific segments of the OLTV and DTI that are not well explained by the model. The Pearson residual for the *i*th observation is constructed as follows:

$$c_i = \frac{\sqrt{w_i}(1 - p_i)}{\sqrt{p_i(1 - p_i)}}$$

Where w_i is the weight of each loan i and p_i is the probability of default for loan i. In our case, every loan has the same weight (i.e. weight=1). Higher residuals for specific observations mean that the model performs a poor job in explaining the default behaviour for these loans. We computed the Pearson residual on a loan by loan basis for the regression models reported in Table 12, 14 and 15 and then computed the average (median, 1 percentile, 99 percentile, among others) for various OLTV and DTI buckets. As a further check we also compute the Kuipers Score. The Kuipers Score (*KS*), for two events with base probability of ½ each is defined as the difference between the proportion of correct predictions of an event and the proportion of false predictions when the alternative event occurred i.e. it is defined as the difference between the hit rate and the false alarm rate. Similar to the Pearson residuals, we calculate the KS for each OLTV and DTI bucket. The higher the KS, the better is the prediction of the model for the subset analysed.

The Pearson residual analysis are reported in figure 14-19 and Kuipers-Score are shown in Table 18-23. The results broadly show poor model fit (high residuals, low KS) for some of the low OLTV segments (0-40) and low DTI segments (<20%). In most cases we have limited data on extremely high OLTVs (>100%) and so we were unable to test for the model fit for this segment. In the prime data we find the KS is lower at the high OLTVs indicating a poor model fit for OLTVs>90%. Overall, though the performance of the regression model at higher OLTV and DTI is comparatively better than at lower OLTV and DTIs.

5 Discussion and Concluding Remarks

5.1 Key findings

Our study broadly confirms many conventional assumptions on the relative default risk of UK mortgage loans. In particular, we find that some risk factors commonly viewed as most important for the risk assessment are indeed reliable predictors of relative risk for both the prime and the non-conforming sector, in particular the original loan-to-value ratio and to some degree the debt-to-income ratio. We also find that the separation into prime and subprime lending can be justified on the grounds that adverse credit information is a major predictor of default. Otherwise, standard indicators of relative risk, such as interest-only loans, self-certification and self-employment can be confirmed in this study. The study does not confirm that non-income verification as done for fast track mortgages in the prime sector is similarly detrimental as is the option of self-certification in the non-conforming sector.

In addition we are able to show that most risk factors are robust to the default definition, i.e. there is no significant difference between the results on 90ever delinquencies and repossessions. This is helpful for future research as delinquency data are more abundant and leading indicators compared to repossessions which are recorded only with several months delay. Few exceptions to this are the limited explanatory power of the debt-to-income ratio and the strong positive significance of the indicators for buy-to-let and right-to-buy mortgages in the repossession data.

Finally, despite the limited time span of our data history we can also identify some trends of risk indicators over time. For example, we identify an adverse trend with loans secured by new build properties towards the vintages 2006 and 2007 which can be attributed to a loosening of underwriting procedures at the time. We expect, however, that this has been reversed with the onset of the economic crisis and the subsequent significant tightening of underwriting criteria across all UK lenders. We also identify over time an increasing impact of self-employment on defaults which can be explained with a higher income sensitivity of self-employeds on the general economic environment compared to employees.

5.2 Comparison to other countries

Mortgage markets can be very heterogeneous across the world. Loan products, supply and demand of housing and credit availability can differ substantially among the various structures of financial markets. While the focus of this paper is on the UK mortgage market, it is useful to compare the drivers of default identified in this study with experiences made in other countries. For this purpose we also studied loan-level data on mortgage performance from other countries. The data are less abundant and in some cases limited to only few originators per country, but still provide useful benchmark information to compare the results from this study with. A separate publication on the findings with more detail about the datasets and methodologies used is planned for the near future.

Table 24 summarises some key findings (using logistic regression analysis) with respect to the predictors of default across various European countries and the US. We pool our results from internal Fitch Ratings studies with those from the Demyanyk and Hemert (2009) study on the US and Diaz-Serrano's (2005) study on several European countries. While the US study is based on loan-level performance data using delinquency and foreclosure rates that covers half of the US subprime market, the European study uses a household panel survey for eight European countries that includes information on mortgage payment problems. Aggregating the findings across studies we find, surprisingly, that for the most part no major divergences between the findings for the countries exist, despite the heterogeneity in regulatory framework, market practices and cultural background. The two most important drivers across all countries are household equity and ability-to-pay. [24]

The key differences arise in terms of the effects of the various products and loan characteristics that differ across countries. In some instances similar products are riskier in some countries than others due to the differing structure of the mortgage market. For example, as the UK mortgage market is predominantly floating rate we do not find floating rate loans to be more risky than fixed-rate loans. However, in other European countries which have a mix of floating and fixed rate loans, the marginal effect of floating rate loans was statistically and economically significant.

5.3 Future outlook

Limitations of this study result mainly from having only four years of origination vintages with a sufficient breadth of observations and a limited number of years of performance information. One extension of this study would result from replicating this analysis once data are available over a longer time horizon. This would allow for insights into default timing by borrower and product type as well as the study of borrower behaviour throughout a business cycle at a loan-level. On a technical level – if supplemented with prepayment information – longer-running mortgage default data would allow the study of competing risks models which additionally capture the interdependency of default likelihood with likelihood of prepayment.

As mortgage credit risk is driven equally by loss severities as it is driven by default rates a study on determinants of loss severities would provide a useful complement to

[24] Note: Diaz-Serrano (2005) do not include OLTV in the regression analysis due to data limitations.

this study. Such an analysis based on a similarly composed pool of data on defaulted mortgage loans in the UK is underway.

Furthermore, a comparison to other countries would not only benefit the understanding of the UK mortgage risk but also help to develop a comprehensive understanding of risk factors across jurisdictions and market setups. Such a cross-country study would lead to important insights into the dependency between the housing market framework and credit risk and could feed into policy recommendations of governments and financial regulators.

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Tables and Charts

Table 1: Number of Loans by Transaction Series

A. Number of Loans by Transaction Series (Non-Conforming)

	Repossession Information	Arrears Information
Bluestone	7,767	7,767
Eurosail		16,231
Leek	21,461	11,709
Ludgate		1,447
Mansard	3,271	1,935
Money Partners	10,062	
RMAC	12,895	4,957
RMS	13,053	
Total	68,509	44,046

B. Number of Loans by Transaction Series (Prime)

Arkle	314,874
Arran1	25,316
Gracechurch	72,508
Granite	285,159
Total	697,857

Table 2: List of Transactions in each Transaction Series

Transaction	Transaction Series
Bluestone041	Bluestone
Bluestone061	Bluestone
Bluestone071	Bluestone
esail061	Eurosail
esail063	Eurosail
esail071	Eurosail
Leek 14	Leek
Leek 20	Leek
Leek 21	Leek
Ludgate061	Ludgate
Mansard061	Mansard
MPS1	Money Partners
MPS2	Money Partners
MPS3	Money Partners
MPS4	Money Partners
Rmac061	RMAC
Rmac062	RMAC
Rmac063	RMAC
RMS21	RMS
RMS22	RMS

Table 3: Number of Loans by Origination Vintage

Number of Loans	Non-Conforming		Prime
	Repossession Information	Arrears Information	Arrears Information
Missing	2,599	2	-
Pre 2000	307	15	48,302
2000-2002	2,595	913	95,811
2003	966	966	59,071
2004	1,656	1,999	88,615
2005	12,503	4,295	120,586
2006	31,710	27,779	188,080
2007	16,173	8,077	97,392
All	68,509	44,046	697,857

Table 4: Number of Loans by Year of Repossession

Repossession Year	Number of Loans	% of Total
2004	2	0.07%
2005	92	3.39%
2006	407	15.01%
2007	977	36.03%
2008	1174	43.29%
2009	60	2.21%

Table 5: Average OLTV by Origination Vintage

	Non-Conforming		Prime
	Repossession Information	Arrears Information	Arrears Information
Pre 2000	64.7%	75.5%	61.0%
2000-2002	68.7%	68.2%	62.4%
2003	72.9%	73.0%	62.0%
2004	72.7%	73.1%	64.8%
2005	73.5%	76.2%	70.6%
2006	77.0%	75.3%	70.1%
2007	81.9%	82.5%	69.3%

Table 6: Average DTI by Origination Vintage

	Non-Conforming		Prime
	Repossession Information	Arrears Information	Arrears Information
Pre 2000	30.1%	40.8%	30.0%
2000-2002	33.9%	30.8%	31.3%
2003	33.8%	33.7%	32.9%
2004	35.7%	35.2%	33.6%
2005	35.6%	35.0%	35.6%
2006	35.5%	36.8%	35.8%
2007	36.4%	37.2%	36.0%

Table 7: Distribution of Loan Characteristics

	Non-Conforming		Prime
Characteristics	Repossession Information	Arrears Information	Arrears Information
Self Employed	31.3%	39.1%	10.8%
Self Certification	59.8%	61.4%	
Fast Track	0.0%	0.0%	16.5%
Interest Only (owner-occupied)	50.4%	50.3%	26.4%
Interest Only (BtL)	89.5%	90.8%	0.0%
Remortgage Loans	59.3%	57.2%	39.2%
Right to Buy	6.6%	18.9%	0.0%
Buy to Let	6.6%	6.5%	0.0%
New Builds	7.1%	6.1%	8.8%

Table 8: Adverse Credit Characteristics in Non-Conforming Sector

	Non-Conforming Repossession Information	Non-Conforming Arrears Information
Adverse Credit	26.1%	42.0%
Country Court Judgement (CCJ)	18.0%	28.7%
Arrears in the last 7-12 months before origination	7.2%	7.9%
Arrears in the last 0-6 months before origination	6.0%	5.9%
Bankruptcy or Individual Voluntary Arrangement (IVA)	1.5%	2.2%

Table 9: T-Tests - Repossession Rates by Product and Borrower Characteristics

Non-Conforming Repossession Information	Y	N	T-Test significance
Self Employed	7.3%	3.8%	***
Self Certification	6.1%	4.0%	***
Interest Only (owner-occupied)	6.5%	4.2%	***
Remortgage Loans	5.6%	4.8%	***
Right to Buy	1.9%	5.5%	***
Buy to Let	5.0%	5.3%	NS
New Builds	10.0%	4.9%	***
Adverse Credit	7.1%	4.7%	***
Bankruptcy or Individual Voluntary Arrangement (IVA)	3.8%	5.3%	**
Country Court Judgement (CCJ)	8.2%	4.6%	***
Arrears in the last 7-12 months before origination	3.8%	5.3%	***
Arrears in the last 0-6 months before origination	9.4%	4.9%	***

Table 10: T-Tests – Non-conforming 90ever rates by Product and Borrower Characteristics

Non-Conforming Arrears Information	Y	N	T-Test significance
Self Employed	24.4%	22.0%	***
Self Certification	26.1%	19.4%	***
Interest Only (owner-occupied)	24.8%	22.4%	***
Remortgage Loans	28.0%	17.6%	***
Right to Buy	26.9%	22.8%	***
Buy to Let	20.8%	23.7%	***
New Builds	20.0%	23.8%	***
Adverse Credit	31.1%	18.1%	***
Bankruptcy or Individual Voluntary Arrangement (IVA)	18.9%	23.7%	***
Country Court Judgement (CCJ)	37.3%	18.3%	***
Arrears in the last 7-12 months before origination	32.2%	21.8%	***
Arrears in the last 0-6 months before origination	32.0%	22.0%	***

Table 11: T-Tests – Prime 90-ever Rates by Product and Borrower Characteristics

Prime	Y	N	T-Test significance
Self Employed	2.8%	2.3%	***
Fast Track	1.9%	2.4%	***
Interest Only (owner-occupied)	2.9%	2.1%	***
Remortgage Loans	1.4%	1.1%	***

Table 12: Regression Results for 90ever Arrears on Prime Loans

	2004	2005	2006	2007	All Vintages
OLTV	0.48%***	0.23%***	0.54%***	0.37%***	0.66%***
DTI	-0.10%***	-0.06%***	-0.11%***		-0.11%***
Fast Track	-0.21%***	-0.15%***	-0.32%***	-0.27%***	0.31%***
Self Employed	0.18%***	0.14%***	0.38%***	0.34%***	0.34%***
Interest Only	0.42%***	0.16%***	0.28%***	0.14%***	0.49%***
$\text{Pr(arrears)}_{\text{x at mean}}$	1.17%	0.57%	1.58%	1.26%	1.70%
Transaction Dummies	Yes	Yes	Yes	Yes	Yes
N	88615	120586	188080	97392	697857
R-squared	0.1301	0.1065	0.0826	0.0511	0.0908

The table reports marginal effects from the logistic regression using >3 month arrears in prime sector as a dependent variable (intercept is not reported). The marginal effects for OLTV and DTI measure the effect of a 10% increase in the explanatory variable, while marginal effects for stabilised margin measure the effect of a 1% increase in the explanatory variable. The categorical variable marginal effect represents the difference in probability of arrears when the categorical variable is 1 and 0. Pr(arrears) states the probability of arrears using the logistic regression parameters where OLTV, DTI are evaluated at their means and categorical variables at zero. ***,**,* represent statistical significance at 1%,5% and 10% levels respectively.

Table 13: Regression Results for 90ever Arrears on Prime Loans: Including Remortgage and Stabilised Margin

	2004	2005	2006	2007
OLTV	0.50%***	0.23%***	0.18%***	0.07%***
DTI	-0.07%**	-0.03%**		0.02%**
Remortgage	0.54%***	0.28%***	0.32%***	0.05%***
Fast Track		-0.32%***	-0.31%***	-0.13%***
Self Employed		0.05%*	0.10%***	0.03%**
Stabilised Margin	0.24%***		0.26%***	
Interest Only	0.23%***	0.08%***	0.04%***	
Pr(arrears)$_{x \text{ at mean}}$	1.09%	0.54%	0.50%	0.21%
Transaction Dummies	Yes	Yes	Yes	Yes
N	58187	56479	86057	53417
R-squared	0.0635	0.0655	0.0737	0.0559

The table reports marginal effects from the logistic regression using >3 month arrears in prime sector as a dependent variable (intercept is not reported). The marginal effects for OLTV and DTI measure the effect of a 10% increase in the explanatory variable, while marginal effects for stabilised margin measure the effect of a 1% increase in the explanatory variable.. The categorical variable marginal effect represents the difference in probability of arrears when the categorical variable is 1 and 0. Pr(arrears) states the probability of arrears using the logistic regression parameters where OLTV, DTI and stabilised margin are evaluated at their means and categorical variables at zero ***,**,* represent statistical significance at 1%,5% and 10% levels respectively.

Table 14: Regression Results for 90ever Arrears on Non-Conforming Loans

	2005	2006	2007	All Vintages
OLTV	5.02%***	4.64%***	1.21%***	3.39%***
DTI		0.97%***	1.08%***	0.84%***
New Build		7.31%***	3.81%**	
Adverse Credit	13.37%***	5.48%***	8.02%***	7.40%***
Remortgage	5.73%***	1.82%***	4.07%***	2.42%***
Adverse Credit * Remortgage		3.84%***		1.74%***
Self Certified		2.03%***	-1.62%***	0.56%***
Adverse Credit * Self Certified		1.50%**	1.76%**	1.96%***
Self Employed	4.54%***	1.48%***	1.54%***	1.20%***
Interest Only	2.4%**	0.9%***	0.8%**	1.2%***
Pr(arrears)$_{x \text{ at mean}}$	23.8%	22.0%	9.1%	15.5%
Transaction Dummies	Y	Y	Y	Y
N	2993	19549	7086	30892
R=squared	0.1737	0.2393	0.0651	0.2223

The table reports marginal effects from the logistic regression using >3 month arrears in non-conforming sector as a dependent variable (intercept is not reported). The marginal effects for OLTV and DTI measure the effect of a 10% increase in the explanatory variable. The categorical variable marginal effect represents the difference in probability of arrears when the categorical variable is 1 and 0. Pr(arrears) states the probability of arrears using the logistic regression parameters where OLTV, DTI are evaluated at their means and categorical variables at zero. ***,**,* represent statistical significance at 1%,5% and 10% levels respectively.

Table 15: Regression Results for Repossession on Non-conforming loans

	2005	2006	2007	All Vintages
OLTV	3.31%***	5.17%***	0.13%***	5.86%***
DTI		0.53%***		-5.57%***
New Build		3.23%*		-3.48%***
Adverse Credit	3.92%***	5.18%***	0.97%***	5.86%***
Remortgage	0.46%***	0.84%***	0.25%	2.46%***
RTB	1.28%***	2.07%***		2.09%***
BTL	1.05%***	2.73%***	-0.18%*	0.77%***
Self Certified	0.16%	0.66%***	0.10%*	0.81%***
Adverse Credit * Self Certified	0.52%**			1.15%***
Interest Only	0.37%***	0.86%***	0.11%**	0.89%***
$Pr(Repossession)_{x \text{ at mean}}$	2.29%	5.26%	0.37%	6.00%
Transaction Dummies	Y	Y	Y	Y
N	11902	29042	16173	65238
R-squared	0.1644	0.1376	0.11	0.1015

The table reports marginal effects from the logistic regression using repossessions in non-conforming sector as a dependent variable (intercept is not reported). The marginal effects for OLTV and DTI measure the effect of a 10% increase in the explanatory variable. The categorical variable marginal effect represents the difference in probability of repossession/arrears when the categorical variable is 1 and 0. Pr(repossession) states the probability of repossession using the logistic regression parameters where OLTV, DTI are evaluated at their means and dummy variables at zero. ***,**,* represent statistical significance at 1%,5% and 10% levels respectively.

Table 16: Regression Results for Repossession and 90ever Arrears in Non-Conforming: Reduced Sample

	Repossession	**90ever**
	Repossession Information	Arrears Information
OLTV	0.52%***	3.07%***
DTI	0.06%***	1.61%***
New Build		5.47%***
Adverse Credit	0.29%***	9.91%***
Self Certified	0.05%*	0.61%
Adverse Credit * Self Certified	0.12%**	2.22%***
Remortgage	0.11%***	2.08%***
Interest Only	0.12%***	3.07%***
$Pr(default)_{x \text{ at mean}}$	0.30%	11.64%
Transaction Dummies	Yes	Yes
N	21950	21950
R-squared	0.2475	0.2223

The table reports marginal effects from the logistic regression using repossession and 90ever in non-conforming sector as a dependent variable (intercept is not reported). It uses a reduced sample of loans where both repossession and 90ever indicator were available. The marginal effects for OLTV and DTI measure the effect of a 10% increase in the explanatory variable. The categorical variable marginal effect represents the difference in probability of repossession/arrears when the categorical variable is 1 and 0. Pr(defaults) states the probability of repossession/arrears using the logistic regression parameters where OLTV, DTI are evaluated at their means and dummy variables at zero. ***,**,* represent statistical significance at 1%,5% and 10% levels respectively.

Table 17: Regression Results for Repossession and 90ever Arrears in Non-conforming loans: Debt-Consolidation Test

	Repossession Repossession Information	**90ever** Arrears Information
OLTV	2.77%***	2.51%***
DTI	-0.53%***	0.49%*
Adverse Credit	2.05%***	4.15%***
New Build		9.64%**
BTL	1.88%***	
Self Certified	0.42%	0.85%**
Adverse Credit* Self Certified	1.00%*	
Interest Only	0.79%***	1.50%***
Remortgage		2.01%***
Debt Consolidation	1.23%***	
$\text{Pr(default)}_{\text{x at mean}}$	10.23%	2.71%
Transaction Dummies	Y	Y
N	9326	12773
R-squared	0.2575	0.1045

The table reports marginal effects from the logistic regression using repossession and 90ever in non-conforming sector as a dependent variable (intercept is not reported). It uses a reduced sample of loans where debt consolidation information was available. The marginal effects for OLTV and DTI measure the effect of a 10% increase in the explanatory variable. The categorical variable marginal effect represents the difference in probability of repossession/arrears when the categorical variable is 1 and 0. Pr(defaults) states the probability of repossession/arrears using the logistic regression parameters where OLTV, DTI are evaluated at their means and dummy variables at zero. ***,**,* represent statistical significance at 1%,5% and 10% levels respectively.

Table 18: Kuipers-Score by OLTV band for Prime 2004, 2005, 2006 and 2007 origination vintage models as reported in Table 12

OLTV	2004	2005	2006	2007
0-40	0.013			0.013
40-50	0.015			0.098
50-60	0.031	0.013	0.002	0.245
60-65	0.155	0.011	0.053	0.244
65-70	0.258	0.022	0.041	0.079
70-75	0.173	0.096	0.078	0.147
75-80	0.194	0.170	0.204	0.124
80-85	0.245	0.201	0.177	0.176
85-90	0.176	0.237	0.172	0.177
90-95	0.188	0.131	0.066	0.079
95-98	0.152	0.087	0.035	0.025

Table 19: Kuipers-Score by DTI band for Prime 2004, 2005, 2006 and 2007 origination vintage models as reported in Table 12

DTI	2004	2005	2006	2007
<=20%	0.394	0.344	0.462	0.367
20%-25%	0.425	0.494	0.506	0.457
25%-30%	0.461	0.449	0.406	0.341
30%-35%	0.380	0.404	0.349	0.362
35%-40%	0.400	0.351	0.318	0.237
40%-45%	0.390	0.316	0.292	0.194
>45%	0.380	0.302	0.265	0.203

Table 20: Kuipers-Score by OLTV band for Non-Conforming 90ever 2005, 2006, 2007 and combined origination vintage models as reported in Table 12

OLTV	2004	2005	2006	All
0-40	0.153	0.224	-0.054	0.043
40-50	0.420	0.224	0.100	0.061
50-60	0.386	0.325	0.090	0.059
60-65	0.313	0.305	0.354	0.061
65-70	0.236	0.343	0.208	0.049
70-75	0.481	0.337	0.243	0.046
75-80	0.260	0.374	0.244	0.052
80-85	0.234	0.368	0.218	0.037
85-90	0.275	0.413	0.235	0.029
90-95	0.360	0.351	0.108	0.040
95-98	0.182	0.355	0.195	0.012

Table 21: Kuipers-Score by DTI band for Non-Conforming 90ever 2005, 2006, 2007 and combined origination vintage models as reported in Table 14

DTI	2004	2005	2006	All
<=20%	0.354	0.412	0.022	0.080
20%-25%	0.272	0.387	0.107	0.097
25%-30%	0.286	0.385	0.227	0.100
30%-35%	0.320	0.396	0.284	0.111
35%-40%	0.258	0.395	0.115	0.125
40%-45%	0.346	0.396	0.200	0.143
>45%	0.378	0.332	0.230	0.140

Table 22: Kuipers-Score by OLTV band for Non-Conforming Repossession 2005, 2006, 2007 and combined origination vintage models as reported in Table 15

OLTV	2004	2005	2006	All
0-40				
40-50	0.104		0.122	
50-60	0.147		0.282	0.079
60-65	0.325	0.121		0.147
65-70	0.334	0.192	0.529	0.285
70-75	0.368	0.256	0.370	0.370
75-80	0.343	0.253	0.522	0.405
80-85	0.212	0.256	0.296	0.329
85-90	0.177	0.238	0.439	0.447
90-95	0.260	0.255	0.350	0.466
95-98	0.284	0.482	0.531	0.684

Table 23: Kuipers-Score by DTI band for Non-Conforming Repossession 2005, 2006, 2007 and combined origination vintage models as reported in Table 15

DTI	2004	2005	2006	All
<=20%	0.212	0.523	0.563	0.598
20%-25%	0.357	0.380	0.305	0.501
25%-30%	0.290	0.382	0.371	0.463
30%-35%	0.319	0.350	0.606	0.473
35%-40%	0.341	0.405	0.204	0.499
40%-45%	0.342	0.387	0.386	0.503
>45%	0.285	0.403	0.442	0.528

Table 24: Cross-Country Comparison of Default Drivers

	UK	US	Portugal	Netherlands	Greece	Germany
OLTV	↑	↑	↑	↑	↑	↑
DTI	↑	↑	↑	↑	NA	↑
Interest Only	↑	↑	↑	NA	NA	↑
Remortgage	↑	↑	NA	NA	↑	NA
Buy to Let	↑	↑	NA	NA	NA	NA
Second Home		↑	↑	NA	NA	NA
Self Employed	NA	NS	↑	↑	↑	↑
Self Certified	↑	↑	NA	NA	NA	NA
Variable Rate Loans	NS	↑	↑	↑	NA (all loans variable rate)	↑
Fixed Rate Loans	NS (v. few long-term fixed rate loans)	↓	↓	↓	NA	↓
Adverse Credit	↑	↑	NA	NA	NA	NA
Flat	↑	↓ (condominium)	NA	NS	NS	↓
Multifamily	NA	↑	NA	NS	NS	↑

* NA=Data not available or the field was not relevant to the particular country; NS=Variable was not statistically significant at 10% or below; ↑ is where the variable increases the probability of default and ↓ is where the variable decreases the probability of default.

Figure 1: Default Rates by Origination Vintage

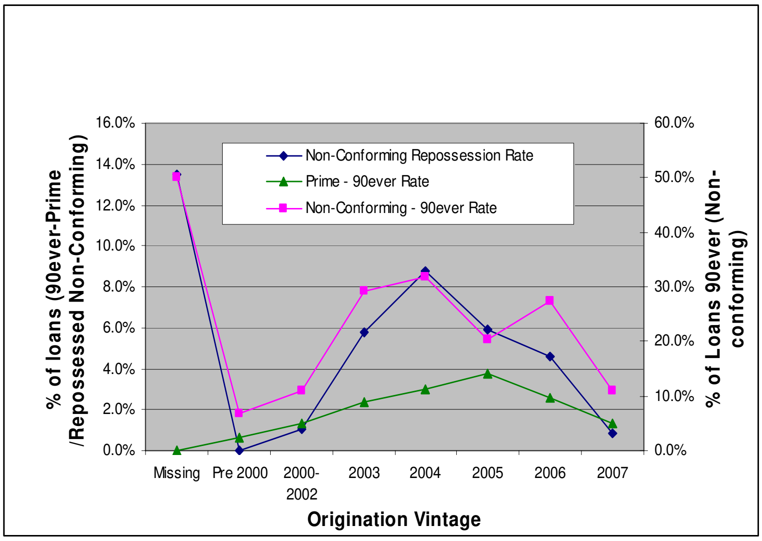

Figure 2: OLTV Distribution by Origination Vintage - Non-Conforming (Repossession Information)

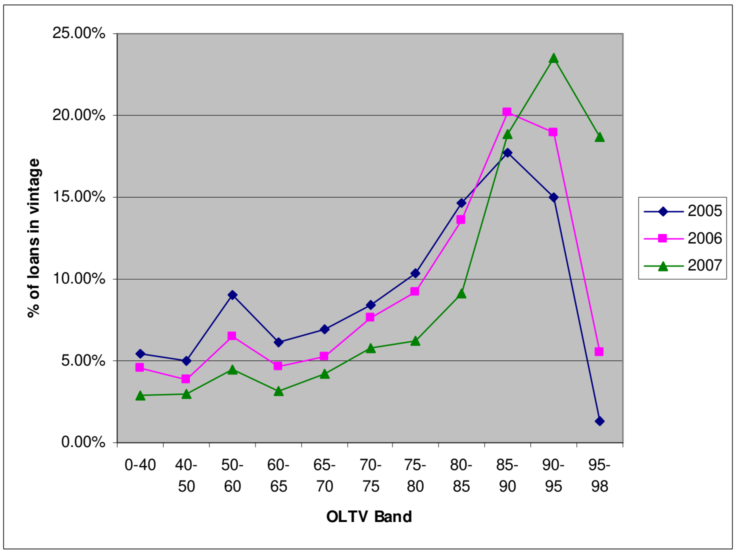

Figure 3: OLTV Distribution by Origination Vintage - Non-Conforming (Arrears Information)

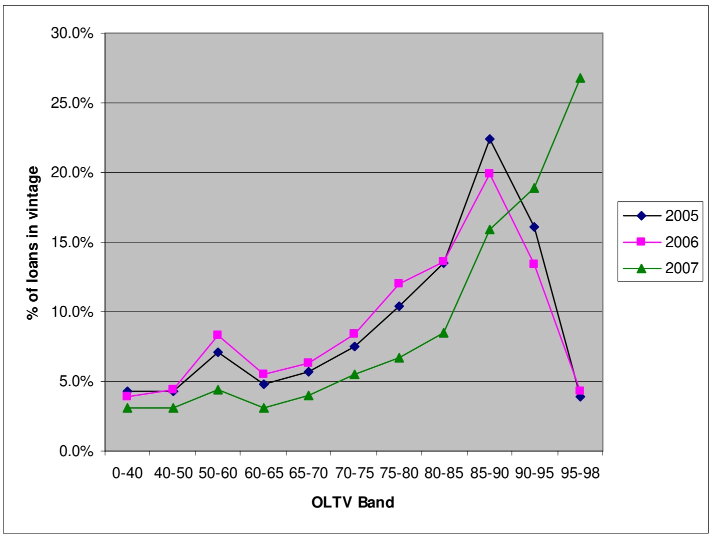

Figure 4: OLTV Distribution by Origination Vintage - Prime

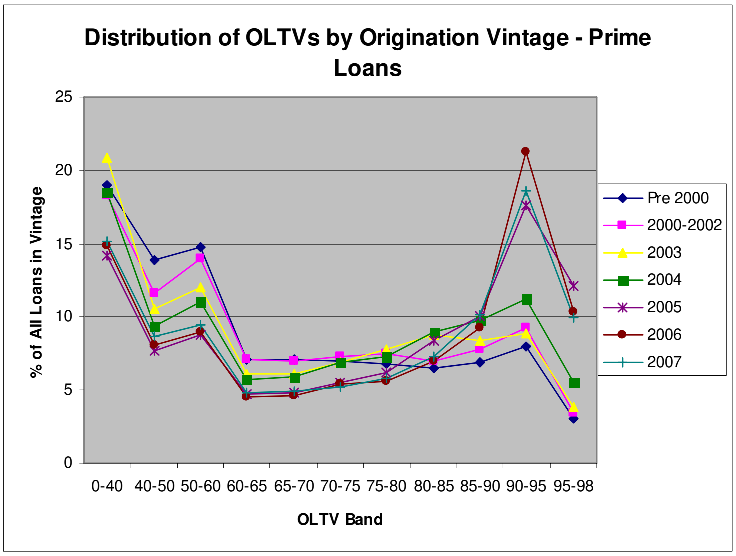

Figure 5: Distribution of DTIs by Origination Vintage - Non-Conforming (Repossession Information)

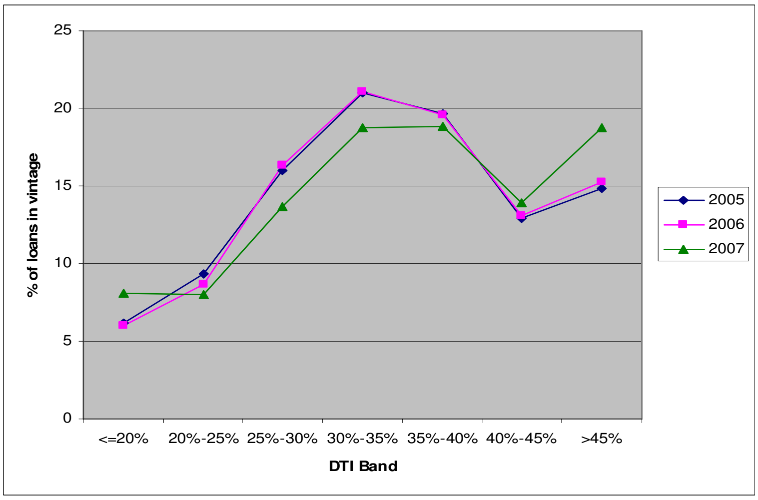

Figure 6: Distribution of DTIs by Origination Vintage - Non-Conforming (Arrears Information)

Figure 7: Distribution of DTIs by Origination Vintage - Prime

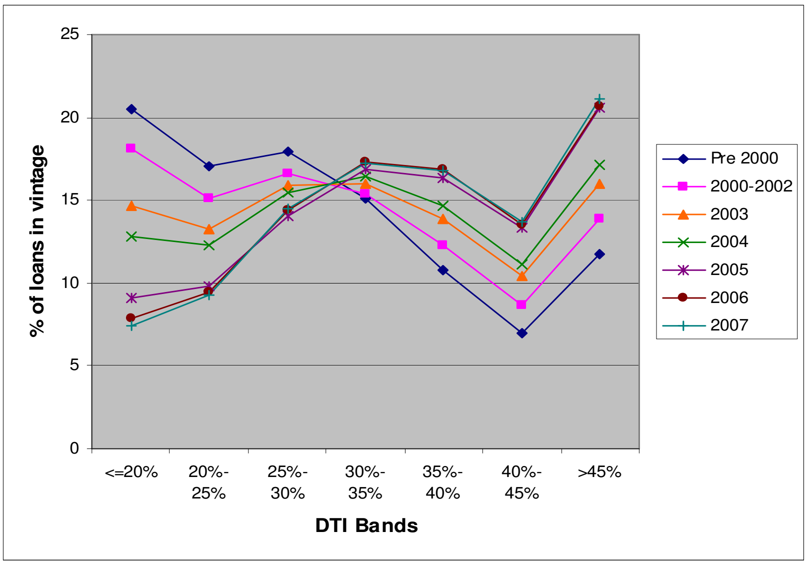

Figure 8: Repossession Rate by OLTV Band – Non-Conforming (Repossession Information)

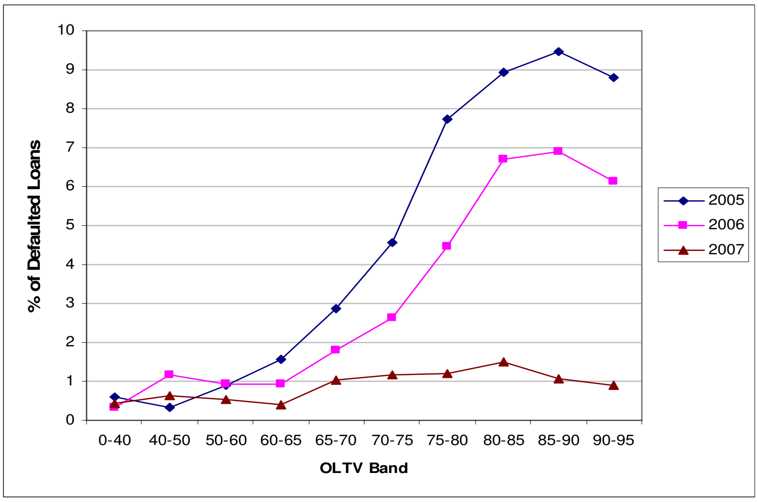

Figure 9: 90ever Rate by OLTV Band – Non-Conforming (Arrears Information)

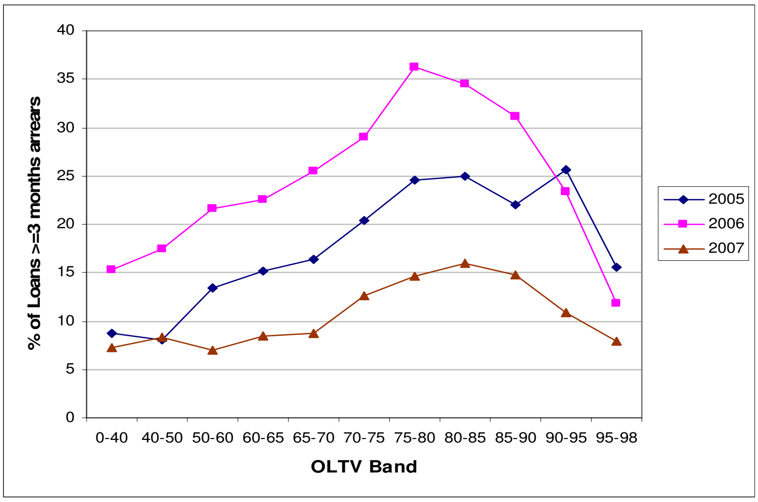

Figure 10: 90ever Rate by OLTV Band – Prime (Arrears Information)

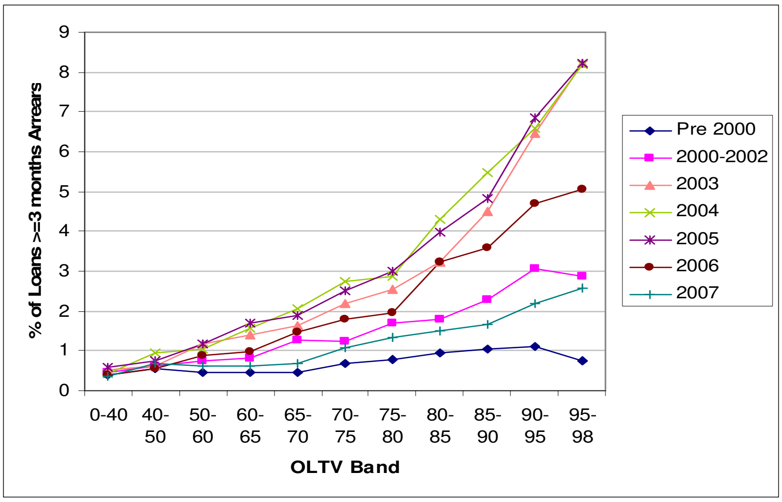

Figure 11: Repossession Rate by DTI Band – Non-Conforming (Repossession Information)

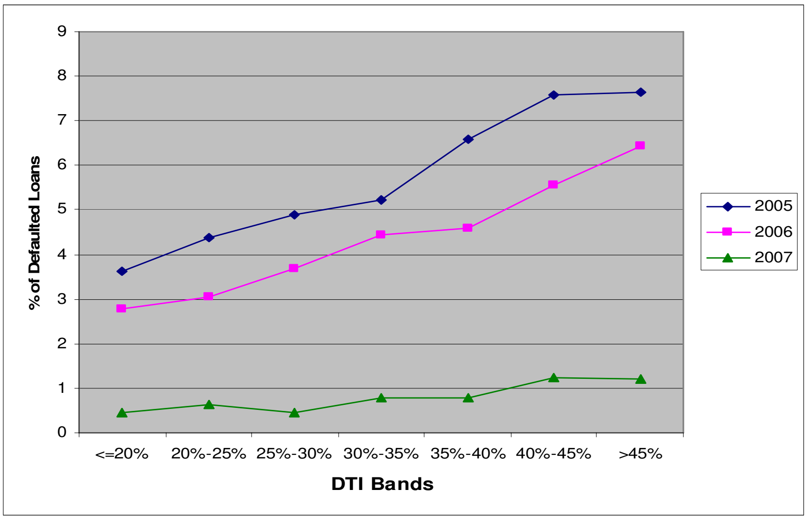

Figure 12: 90ever Rate by DTI Band – Non-Conforming (Arrears Information)

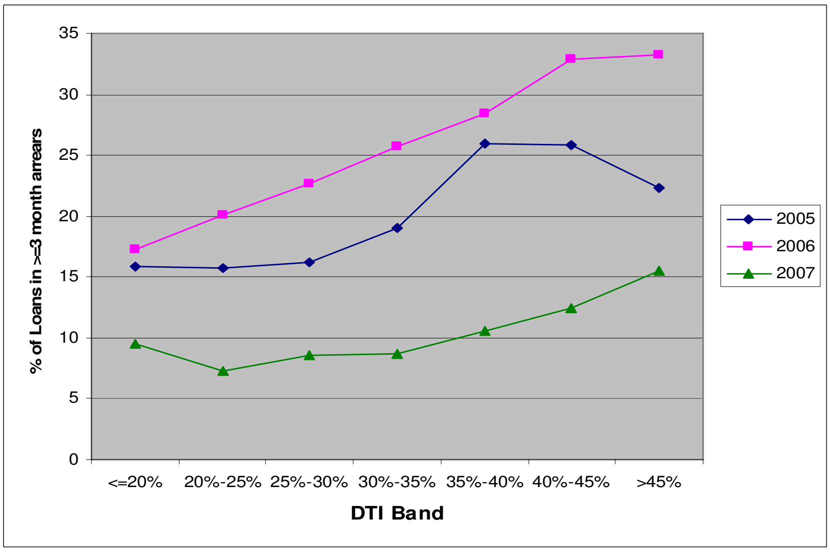

Figure 13: 90ever Rate by DTI Band – Prime (Arrears Information)

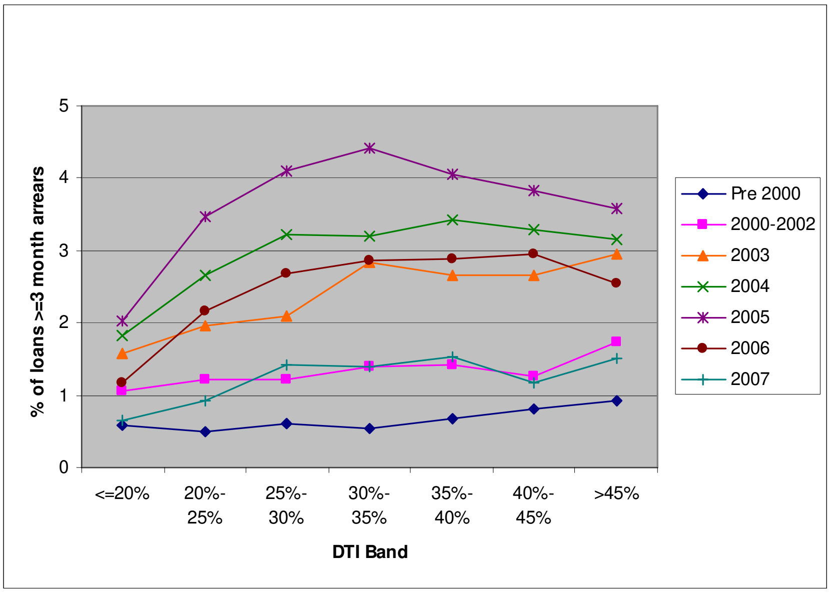

Figure 14: Average Pearson Residuals by OLTV Bucket in Prime Model

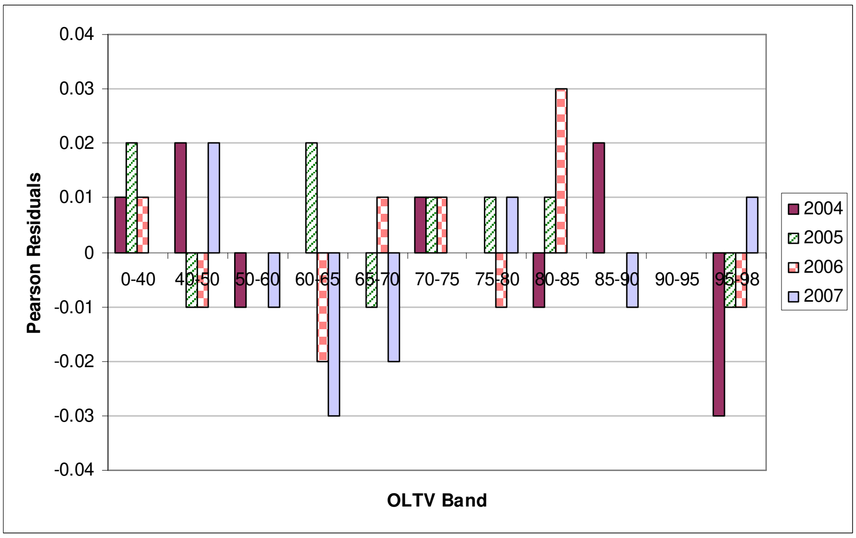

Figure 15: Average Pearson Residuals by DTI Bucket in Prime Model

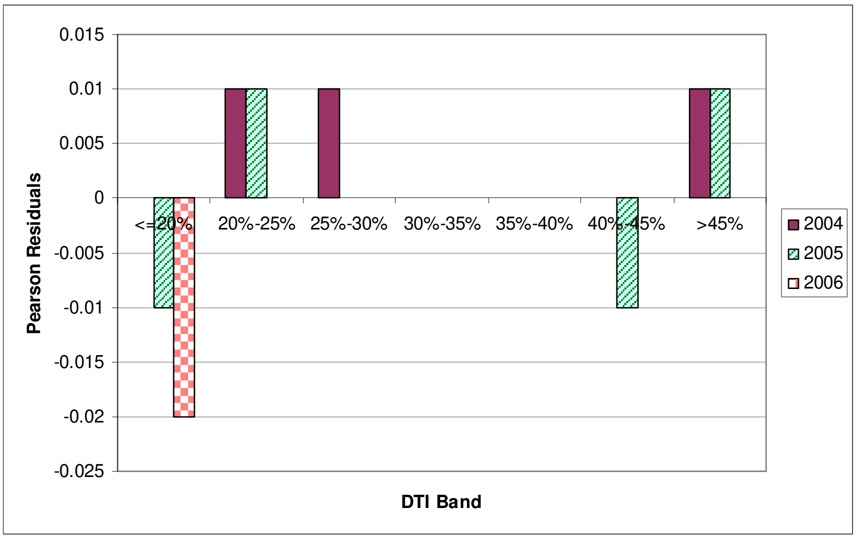

Figure 16: Average Pearson Residuals by OLTV Bucket in Non-Conforming 90ever Model

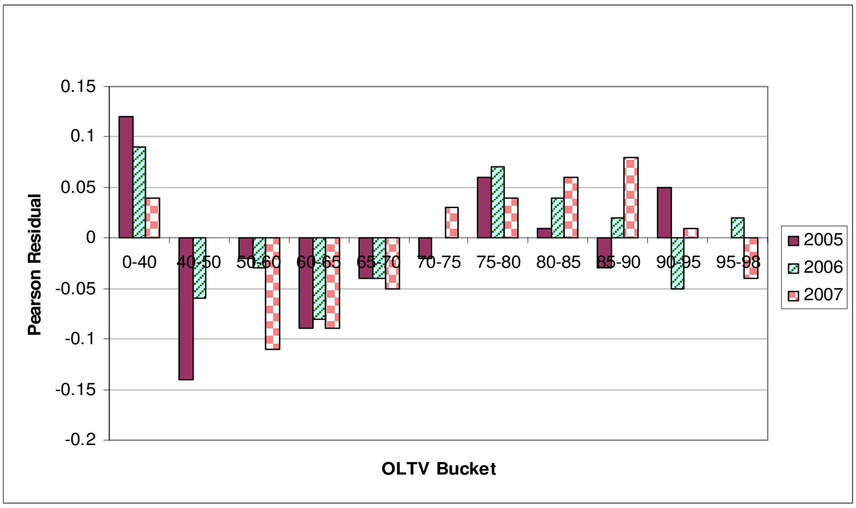

Figure 17: Average Pearson Residuals by DTI Bucket in Non-Conforming 90ever Model

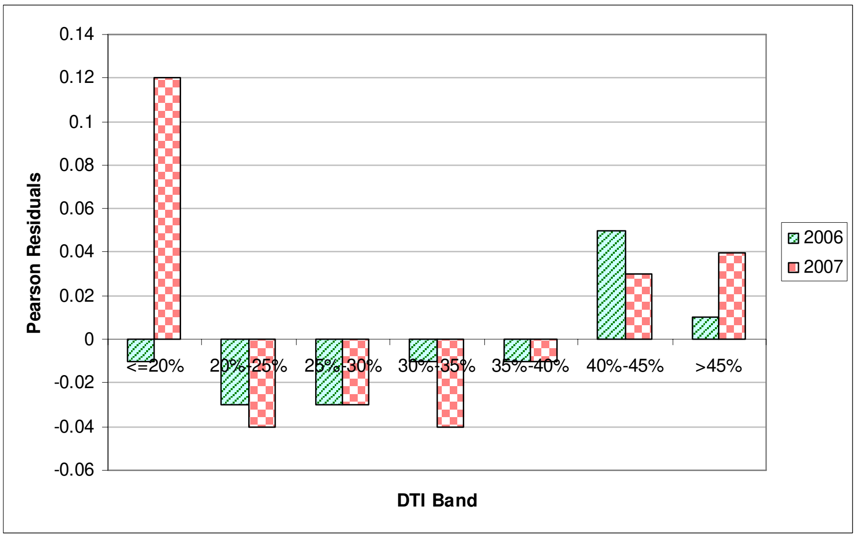

Figure 18: Average Pearson Residuals by OLTV Bucket in Non-Conforming Repossessions Model

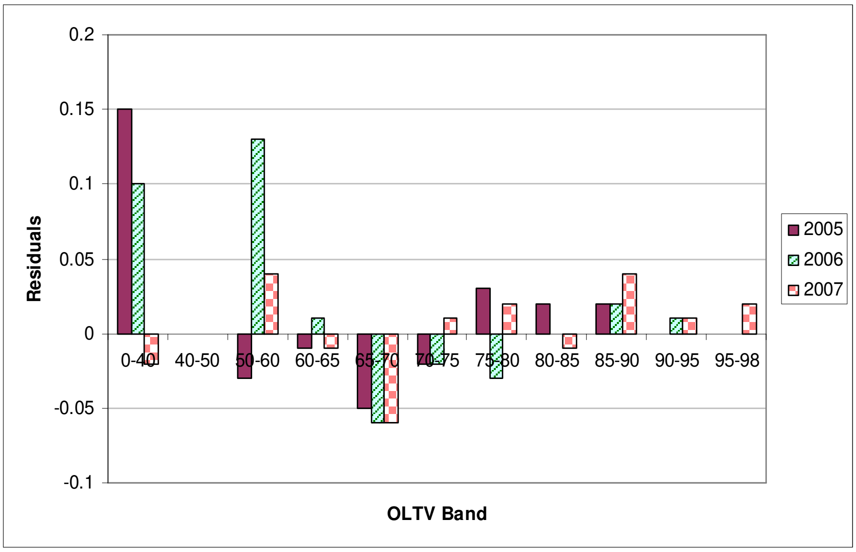

Figure 19: Average Pearson Residuals by DTI Bucket in Non-Conforming Repossessions Model