# Factors Driving Demand and Default Risk in Residential Housing Loans: Indian Evidence

Bandyopadhyay, Arindam and Saha, Asish
National Institute of Bank Management

02. February 2009

# Factors Driving Demand and Default Risk in Residential Housing Loans: Indian Evidence


**Arindam Bandyopadhyay***

***(Associate Professor, Finance, National Institute of Bank Management, Pune, India)***

***&***

**Asish Saha**

***(Director & Professor, National Institute of Bank Management, Pune, India)***


## Abstract


This paper empirically examines the functional role of various micro and macro economic as well as situational factors that determine residential housing demand and risk of borrower default. Using 13,487 housing loan accounts (sanctioned from 1993-2007) data from Housing Finance Institutions (HFIs) in India, we investigate the crucial factors that drive demand for housing and its correlation with borrower characteristics. Next, we examine housing loan defaults and the major causative factors of the same. Our empirical results suggest that borrower defaults on housing loan payments is mainly driven by change in market value of the property vis-à-vis the loan amount and EMI to income ratio. A 10 percent decrease in the market value of the property vis-à-vis the loan amount raises the odds of default by 1.55 percent. Similarly, a 10 percent increase in EMI to income ratio raises the delinquency chance by 4.50 percent. However, one cannot ignore borrower characteristics like marital status, employment situation, regional locations, city locations, age profile and house preference which otherwise may inhibit lender to properly assess credit risk in home loan business as our results show that these parameters also act as default triggers.



**Keywords:** Housing Demand, Risk Management, Financial Institutions and Banks

**JEL Classification Number:** R21, G32, G2


---


* Address for correspondence: Arindam Bandyopadhyay, Associate Professor (Finance), National Institute of Bank Management (NIBM), Kondhwe Khurd, Pune-411048, India. Phone: 0091-20-26716451. ***E-mail addresses:***arindb@rediffmail.com, arindam@nibmindia.org.

## 1. Introduction

The growth in disposable income, demographic changes such as a growing number of working women who spend more, the growing number of nuclear families, higher income levels within the urban population, the access and availability of bank finance are driving the housing demand in India. The housing construction sector is therefore becoming one of the most important sectors of the Indian economy and has tremendous potential to become more and more important in the coming years. However, housing finance companies and banks need to more carefully evaluate the underlying risk of default. Aggressive lending by banks in a soft interest rate environment during early part of the present decade with corresponding sharp growth in hosing construction led to a major supply-demand mismatch in the residential housing market in US. Less than proportionate growth in household income, hardening of the interest rate environment and reduced liquidity in the subsequent period led to a precipitous fall in the market value of the housing stock. The dramatic drop in the residential property rates in many parts of the US is being attributed in the literature to the ongoing 'sub-prime crisis'. It is in this sense essential to understand the basic demand drivers in this market and how they are linked to the default risk of housing loans. The sharp fall in property prices following the Asian financial crisis (June 1997-December 1998) has led many residential mortgage holders in Hong Kong, South Korea, Japan to experience negative equity which had caused sharp increase in non performing assets (NPAs) and severe loan losses.

Banks in India have been playing an important role in providing credit to the housing sector and thereby contributing to the aggregate demand in the sector. Moreover, Indian banks also extend various types of loans against residential housing properties. Housing loan now constitutes more than 25 percent of the lending portfolios of individual banks. While evaluating the loan proposal, banks look at both qualitative and quantitative factors to evaluate the credit worthiness of their customers. Profiling of customers and idea of their changing preference and demand projections would help banks to better understand the market. It is also pertinent to mention at this stage that rapid growth in mortgage credit and house prices has given way to heightened concerns about housing loan defaults. Rapid expansion of credit increases the possibility of relaxation of income criteria/lending standards for those applying for loans or lending to those whose income stream is not guaranteed or secure. Variation in standards across the industry imposes systemic risks which can be a potential threat to the sector. As identified by Ellis (2008, BIS paper), the US mortgage system had previously tended to lend at more conservative (Tsatsaronis and Zhu (2004)), however, at later phase, LTV ratios on new mortgages increased substantially, and explicit 100 percent financing became much common. This easing of lending norms is one of the major driver of observed increase in early payment defaults in the United States (Kiff and Mills 2007; Gerardi, Lehnert, Sherlund and Willen, 2008). Ellis (2008) has shown that lending standards declined more in areas that experienced larger credit booms and house price increases.

Recent US mortgage crisis, which has virtually crippled the health of the financial system, sends a clear signal that due-diligence in lending should continue to be the corner stone of sound banking practices. It has further revealed the vulnerability of the financial institutions due to interaction between falling housing prices and homeowners' home equity lines of credit.[1] As housing prices have risen over the course of the current decade, products have proliferated that allow consumers to tap into the wealth created by home-price appreciation and in the process their mark to market loan to value ratio was steadily increasing. These products became potentially risky during periods of falling home prices (Rosengren, 2008).

The empirical research on housing market in India is scarce due to the paucity of relevant data. The main objective of this paper is a) to find the nature of residential housing demand at present in India and estimate the major factors that drive the residential housing demand, b) to correlate existing profile of housing loan borrowers of select banks and housing finance companies to understand the relationship between borrower characteristics and loan parameters such as asset quality, delinquencies, period of loans, collateral values etc. c) Type of households in the population more prone to default on payments, d) How demographic and situational factors such as employment status, family type, income level, locations affect risk of default. In doing so, we also examine the linkage between loan delinquency and value of collateral to further pinpoint the importance of valuation in the housing sector.

In order to accomplish the above objectives, present study uses individual account level loan data from banks and housing finance companies and macroeconomic information collected from various secondary sources to examine the determinants of residential housing demand and default risk in India. Apart from macroeconomic variables, loan related, situational and locational factors are used as explanatory variables.

---

[1] On a national level, housing prices peaked in early 2005, began declining in 2006 and have not yet bottomed. Increased foreclosure rates in 2006–2007 by U.S. homeowners led to a crisis in August 2007 for the sub-prime mortgage market.

The rest of the paper is organized as follows. Next section discusses the relevant literature on housing demand estimation and key risk factors embedded in this market and nature of their relationship. The third section gives a macro perspective on the housing market condition in India that will enable the reader to assess the market and industry attractiveness. The fourth section describes the data, construction of variables and descriptive statistics. The fifth section presents the empirical results. Section six discusses the main conclusions. Tables and Figures are given at the end of the paper with a list of variables and their definitions.

## 2. Review of Literature

Most of empirical studies on estimation of housing demand take price, income and demographic parameters either in a log-linear regression or in a two-stage hedonic pricing regression method (Rosen, 1974; Brown and Rosen, 1982; Epple, 1987; Bartik, 1987; Bajari and Kahn, 2003. Tewari and Parikh (1998 and 1999) have used ridge regressions function (log-linear) to estimate housing demand. Bajari and Kahn (2003) estimated the hedonic price functions to predict the distribution of taste parameters as a function of demographics. Arimah (1992) estimated demand functions for a set of housing attributes for the city of Ibadan in Nigeria using a two-step method like Rosen (1974). Their empirical results reveal that the most important determinants of the demand attributes are: income, price, household size and the occupational status of the head of household. Besides income and wealth, other characteristics (sociological or demographic) of the household may influence the difference in housing demands. The number of people in the household influences the consumption demand positively (more spacious housing). Moreover, the nature of professional activity (employee vs. self-employed) and professional status (retired vs. in activity) also can affect housing demand. The stock value of financial information (proxied by age, education, etc.) may also explain housing demand. In this paper, we have performed a panel Least Square Dummy Variable (LSDV) regression method using 13,487 borrower account data to study the effect of income, price, and age on housing demand. In our micro model, we have considered natural log of house area (in square meter) as proxy for housing demand. We have also captured various location related variables, and studied their influence on demand for dwelling units.

Much of the research on housing loan default has tested the relative importance of negative equity (or loan to value ratio) and factors related to the borrowers' ability to pay as determinants of mortgage default. There is empirical evidence to show that variance in property value (uncertainty) is related to default risk. Furstenberg (1974), Morton (1975), Ingram and Frazier (1982), Webb (1982), Waller (1988), Canner et al. (1991), Vandell, Barnes, Hartzell, Kraft and Wendt (1993) and Lawrence and Arshadi (1995) and have found that in addition to borrower's personal characteristics, Loan to Value (LTV) ratio at the time of origination as well as the income of the borrower play important roles in mortgage delinquency. Campbell and Dietrich (1984), Vandell and Thibodeau (1985), Lawrence et al. (1992), Mills and Lubuele (1994) and Deng et al. (1995) all concluded that the variable "loan-to-value ratio" has made a statistically significant contribution to the determinants of mortgage loan default risk and also showed that their relationship is positively correlated.

Lee (2002) has identified the 'purpose of purchasing real estate property' is one of the key determinants of default risk. If the borrowers purchase new houses for the purpose of personal investment instead of owner-occupied housing, then they will transfer part of their risk to the financial institutions by paying smaller down payments and decreasing their initial equity commitment as much as possible. Therefore, when the market price of collateral falls sharply or economic performance becomes much worse, the property frequently will be abandoned by the owners thereby limiting their loss.

Getter (2003) complemented these finding by using the 1998 Survey of Consumer Finances to show that borrowers use other non-housing financial assets to help make payments during unexpected periods of financial stress. Consistent with prior findings, Chinloy (1995) found that in the United Kingdom during the period 1983 through 1992, LTV and income were the primary covariates associated with delinquency. Other reported studies have also found that credit scores, contemporaneous economic conditions, and the incentive structure of the lender all can impact delinquency (Baku and Smith 1998, Calem and Wachter 1999, Ambrose and Capone 2000).

Another variable, payment-to-income ratio (or Equated Monthly Installment-EMI- to Income ratio), is important in explaining default risk, as confirmed by studies such as Stansell and Millar (1976), Vandell (1978) and Ingram and Frazier (1982). They hold the belief that the higher the payment-to-income ratio, the larger the default risk. Williams, Beranek and Kenkel (1974) have found that once initial payment to income ratio exceeds 30 percent, borrowers tend to have higher probability of default.

Follian, Huang, and Ondrich (1999) include in their model tenure, location, demographic and economic variables as covariates to explain default. The contingent claim approach, which is considered by Kau and Keenan (1998), treats default as a rational decision, such that a default occurs if the house value (equity value) falls below the value of the mortgage. Lee (2002) has empirically proved that residential foreclosure rates are negatively related to local economic diversification.

Studies of von Furstenberg and Green (1974), Avery et al (2004) have assessed local situational factors as factors of default risk. They find that inclusion of situational factors (like unemployment status, marital status, credit history etc.) and other borrower specific characters (joint account or single account, age, location of the borrower etc.) improves the performance of credit scoring models. Riddiough (1991) has found various trigger events, such as divorce, loss of a job, and accident or sudden death has influence on default behavior. Eichholtz (1995) has observed the relationship between regional economic stability and mortgage default risk in Netherlands.

## 3. Housing Market Condition in India: Emerging trends in housing and housing finance

Given the population growth rate in the Indian economy and the consequential requirement for housing stock, the housing construction sector is increasingly becoming one of the most important sectors of the Indian economy having tremendous potential to become more and more important in coming years. If supply constraints do not get in the way, it has the potential to not only satisfy a key requirement, but also would provide impetus to economic growth.

One of the most significant factors that drove the growth of housing market in India in the recent years was the 'easy availability' of bank finance at 'affordable interest rates' owing to relatively comfortable liquidity position in the banking system and a soft interest rate environment. Housing market in India, as evidenced by the growth in bank exposures to the sector took off mainly since the year 2001 (Table 1). The retail loan portfolios of banks including housing and real estate advances expanded at rates ranging between 22 to 41 per cent since 2001-02 and on an average accounted for 20.5 per cent of the incremental non-food credit during this period (see Table 2). Housing credit has formed a dominant share of overall non-food credit growth in India during the recent years. The rapid growth in housing loan market has been supported, inter-alia, by the growth in the middle class population, favourable demographic structure, rising job opportunities in the metropolitan centres, emergence of a number of second tier cities as upcoming business centres, boom in the IT sector in India and rise in disposable incomes. Furthermore, attractive tax advantages for housing loans make them ideal vehicles for tax planning for salary earners.

[Insert Table 1 & Table 2 here]

### *3.1. Prediction of Realizable Demand for Housing through Mapping the Credit Supply Projections*

We have made an attempt to project realizable demand for housing through credit supply channel till 2012 in Table 3 and Table 4. The first column of table 3 presents the year concerned, second column reports number of housing loans disbursed by PSBs during that year, 3rd column shows HFCs share in total Housing loan credit supply (in percent), 4th column shows HFCs number of loans disbursed, 5th column captures the total number of housing loans. In the 6th column we have tabulated the projected households' numbers in million figures. This annual projection is based on exponential projection of decadal census data. Seventh column represents proportion of loan number to households' number.

[Insert Table 3 & Table 4 here]

The realized demand for housing (in percent) is estimated by dividing the total housing loan numbers by the total households population (column 5÷column 7 of the table 2). If we now multiply this percentage (percent) by the households number in million (column 6 figures), we obtain the estimated potential demand for housing (in million). Table 4 depicts the simulated figures in 3 projected growth scenarios (in terms of per capita growth). These three scenarios are the projected loan number to household number in per cent. If percapita loan number increases at a rate of 2.35 percent, 2.50 percent and 3.30 percent, then the corresponding number of projected housing demand in units will be 5.82, 6.19 and 7.43 million respectively in 2012.

**3.2. Growth profile in Indian housing market and probable causes of concern**

There seems to be quite strong association between the economic growth vis-à-vis the loan outstanding (See Figure 1). This is further corroborated by the fact that when there is a downward spiral in the economy, loan outstanding fell behind the limit sanctioned. This association is more pronounced since 1997 during which banks have increasingly moved towards financing housing demand. It can also be indicated at this stage, the Indian taxation laws also stimulated housing loan demands and banks got it as an additional opportunity to expand their credit portfolio at a reasonable rate.[2] It is interesting to note that between the years 2003-05, the housing loan outstanding overshot limit sanctioned which indicates the incipient delinquency. This probably was the reason why RBI put a break on sharp growth in lending to specific segments which also includes Housing Loans. During times of expansion and accelerated credit growth, there is a tendency to under estimate the level of inherent risk and the converse holds during times of recession. This tendency is not effectively addressed by prudential specific provisioning requirements since they capture risk ex-post but not ex-ante (Reddy, 2005). In the said policy (2005-06), RBI increased the provisioning requirement for standard advances from the existing level of 0.25 percent to 0.40 percent. In the annual

---

[2] Interest on borrowed capital up to a certain limit is allowed as deduction if capital is borrowed for the purpose of purchase, construction, repair, renewal or reconstruction of the house property under Section 24 (b) of the Indian Income Tax (IT) Act. In addition, the principal repayment of the loan/capital borrowed is eligible for rebate under Section 88C of the IT Act, 2005

policy statement for the year 2006-07, RBI increased the general provisioning requirement further to 1 percent (Reddy, 2006).

[Insert Figure 1 here]

Lending to the housing sector creates its own collateral in the form of the primary security**.** This has ramifications when cash transactions are involved, which is customarily necessarily paid by the borrower to the promoter and is not included in the actual purchase price while sanctioning housing loan by banks. This gives the lending institution a greater level of comfort as the borrower now has a higher implicit exposure to the property. While lending to home owners may be a more secure form of credit, for the reasons noted above, a rapid dispensation in such credit inevitably involves features that spell risk. Rapid expansion of the home-loan portfolio (a target-driven approach) by Indian Banks during the recent years might have had adverse effect on the lending disciplines in the form of relaxation in income criterion, scrutiny of the title documents etc. Defaults and foreclosures could increase with adverse consequences for bank profitability and even viability.

Further, as evident from Figure 2, house price index in India moved in line with the economic cycle and this was more pronounced during 2004 onwards when banks stepped up the lending to housing segment. The sharp rise in house price after 2003 is mainly due to rapid growth in bank lending to this segment. The rise in housing prices within a short span of time may encourage speculation which in the long run may prove to be illusive to banks and HFCs. A close watch on the borrower’s leverage position in a rising interest rate environment is therefore a necessity.

[Insert Figure 2 here]

Recognizing these risks, our paper empirically examines various idiosyncratic as well as situational factors that influence housing demand and risk profile of borrowers.

## 4. Data, Variables and Descriptive Statistics

The borrower specific parameters normally used by the HFCs and banks while granting loan and pricing of such loans include ownership pattern, gender, age, income, marital status, occupation, location, service & length of service, number of dependents, collateral information, guarantor etc. apart from property specific information. In all, a random sample of 13,487 borrower details is collected from residential housing loan files of a leading housing finance company (HFC) in India and three public sectors banks of the country (we are calling them together as HFIs). These loans were sanctioned any time between years 1993 to 2007.

Variable definitions and descriptive statistics for the samples used to perform our various empirical tests are reported in Tables 5, 6, 7 and 8. Table 6 documents overall sample statistics. This fairly gives idea about the profile of the borrowers and their distribution. As one can notice, 74.14 percent of the borrowers live in Urban Area, 3.52 percent in Sub-urban area and 22.30 percent in rural location. As far as city-wide distributions of borrowers are concerned, 33.49 percent stay in big cities, 50.41 percent live in Medium sized cities and 16.1 percent from smaller cities. Similarly, one may look at the employment status of the sample customers-90.40 percent of them are employed, 6.70 percent are self employed, 2.40 percent are either unemployed or housewives and 0.50 percent belongs to retired & pensioners group. The average age of the borrowers is approximately 44 years with a standard deviation of 8.49. In terms of percentiles, 75 percentiles of the borrowers are in the age level of below 50 years, and 25 percent are below 35 years of age. The median age of the borrowers is 44 years. If we look at the age slab wise distribution, 33.01 percent of the borrowers in the age range: below 40; 41.08 percent are in 40-50; 23.87 percent in 50-60 and 2.02 percent belongs to the age group of above 60 years. Hence, one may summarize that: a typical home loan borrower would most likely to be a male in the age group of 40-50, although a significant 25 percent were below 35 years of age. This age group would prefer to buy a 700 sq ft (70 square meters) dwelling.

[Insert Table 5 and Table 6 here]

Table 7 depicts the falling trend in average age profile of the housing demand. A statistical un-paired t-test confirms that the year wise fall in average age is significant at 1 percent or better level except between year 2006 and 2007.

The profiles of defaulted and non defaulted (or solvent) borrowers are presented in Table 8. There is significant difference between the two classes of customers. Clearly, solvent group of customers are financially better (in terms of monthly income, asset value, property area etc.) than their defaulted counterparts. The defaulted borrowers significantly have larger number of dependents, lesser number of co-borrowers, and the security margin.

[Insert Table 7 and Table 8 here]

## 5. Empirical results

### *5.1. Household demand estimation-: studying the various demand factors*

We have considered natural log of house area (in square meter) as proxy for housing demand. To study the impact and demand elasticity with respect to various factors, we have performed a Least Square Dummy Variable (LSDV) regression model with various explanatory variables collected from the sample data of housing loan accounts from HFIs studied in this paper.

Table 9 reports the results of log-linear least squares dummy variable (LSDV) panel regression results (with robust standard errors) of inter relationship between various factors and housing demand. The borrower specific fixed effects are captured by 3 ‘property location’ dummies (Urban, Semi-urban and Rural) and 3 ‘regional’ dummies (with respect to city size). The location dummies are indicating the borrower location in either ‘Urban’ or ‘Sub Urban’ or in ‘Rural’ area. (See in Table 9, out of the three property location dummies, PROPLOCND1_ URBAN is being dropped and added with the intercept to avoid multi-collinearity problem). Our results show that if other factors held constant, demand for house area (in square meter) is significantly higher in sub-urban and rural area than in urban areas. Similarly, citizens in smaller and medium cities have greater demand for bigger houses than population in big cities. This supports the view that locational factors have influence in driving housing demand.

[Insert Table 9 here]

One can see from the table 9 that income and price elasticity of demand is less than unity. This implies that with the increase in income of the borrower, demand for house would increase; it but would increase at a less than proportionate rate; same is true with price. It can therefore be concluded that housing demand is income and price sensitive. Since the dependent variable is the logarithm of area of property (LNAREA_HD -proxy the housing demand in terms of area), the regression coefficient of ‘LHOUSEPR_SQM’ (natural log value of house price per square meter of property) can be interpreted as the estimated percentage change in the house demand for a 100 percentage change in house price. Holding other factors constant, an increase in house price by 10 percent, ceteris paribus, results in a 4.59 percent decrease in housing demand as affordability comes down. Similarly, the coefficient of income variable (LN_MINC: natural log of monthly income) in Table 9 captures the impact of income on housing demand. The estimated coefficient 0.599 captures that a10 percent increase in the monthly income of the borrower leads to increase in housing demand area by 5.99 percent.

As far as the other factors are concerned, our results show that the demand for house-size is found to be inversely related with the age of the borrowers, depicting that younger borrowers look for bigger house. Moreover, demand for housing space is also influenced by employment situation as retired and pensioners as well as self employed group demand bigger houses than employed and un-employed group.

The number of dependents (NO_DEPEND) capture the financial liability of the borrower and the negatively significant coefficient implies that more number of dependents in a family reduces the affordability and hence the size of the house.

***5.2. Risk factors in housing loans: Key parameters driving House loan default***

In this section, we study various factors that can cause housing loan default. These factors were collected from the HFC's loan history files. The borrower specific parameters normally used by the HFCs while granting loan and pricing of such loans include age, income, occupation, service and length of service, number of dependents, collateral information, guarantor etc. apart from property specific information. In a set of logistic regressions, we have compared the borrowers in standard category (54 percent of the total sample) with the defaulted counterparts (46 percent of the total sample).

Logistic regression is a simple and appropriate technique for estimating the log of the odds of default as a linear function of loan application attributes:

$$\ln\left[\frac{\Pr ob(Default)}{\Pr ob(Solvency)}\right] = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + ... + \beta_k X_{k.} \quad (1)$$

A logistic model has the flexibility of incorporating both the qualitative and quantitative factors and is more efficient than the linear regression probability model. In a set of logistic regression exercises, we are actually predicting the probability of a housing loan default based on the financial, non financial (qualitative borrower characteristics), situational factors (location and local factors) obtained from the credit files and finally macro economic conditions using a panel data of 13,487 borrowers (46 percent defaulted and 54 percent solvent) for 15 years (1993-2007).

The regression results reported in Table-10 provide evidence of major risk factors in housing loan. Logit model is a limited dependent maximum likelihood regression estimation model (similar to Amemiya, 1981; Maddala, 1983). Regression table (Table-10) is the outcome of a logistic regression on a dummy dependent variable "DDEF" that is equal to '1' if the borrower is in the 'defaulted category' and is equal to '0' if the borrower is 'solvent'. We are actually predicting the odd ratio: Prob (Default/Solvency) on various quantitative factors (like area of plot, security value to loan value, number of co-borrowers etc.) and qualitative variables (like presence of a guarantor, marital status, employment status etc.). Estimated values of the parameters (or Coefficients reported in the 2nd column of table 10) can be used to describe the probability of a borrower to default for a unit change in these parameters. The estimated coefficients actually explain how the probability of default changes with one unit change in the parameters (independent variables).

[Insert Table 10 here]

Table 10 results document that security value (represented by the variable: SECVAL_LOANAMT (or inverse of loan to value ratio or LTV, which is the ratio of original book value of the property to the loan amount) is an important and significant determinant of default risk in housing loan (see the coefficient sign is negative and is significant at less than 5 percent level). This means, higher the security margin available to the bank (real margin in this case), lower is the chance of default in home loan. We have also computed economic significance of SECVAL_LOANAMT on the risk of default in housing loan. The regression coefficient of real margin available or SECVAL_LOANAMT measures the influence of margin on default risk. It explains: A decrease (increase) in security value in proportion to loan amount (or inverse LTV) of 1 unit (or 100 percent), with all other variables held constant, increases (decreases) the odds of default by (0.845-1)×100=15.5 percent (see Table 10).[3] Or, we can say that with 10 percent decrease in security margin over loan amount, the odds of default increases by 1.55 percent.

Interestingly, we observe that (Table 10) house size area (LNAREA_HD) is inversely associated with estimated likelihood of default. That is, Bigger the size of house (in terms of area in square meter), lower is the risk of default in housing loan.

We have also tested the relationship between EMI to Income ratio (EMI_INCR) and default risk. The regression result depict that EMI_INCR is positively associated with the estimated likelihood of default. A 10 percent increase in EMI to Income ratio (EMI_INCR) is estimated to raise the likelihood of default by about 4.50 percent. Given the income level at the time of sanctioning of loan, any increase in financial burden due to other additional personal debt certainly increase probability of default. This result has great implications for the bank's loan monitoring. In a rising interest rate environment, EMI to Income ratio may significantly increase which may raise the risk of default. To keep the EMI burden under

[3] The odds that the dependent variable takes the value 1 changes by a factor of exp (-0.169)-1=0.845-1=-0.155 with 1 unit change in SECVAL_LOANAMT.

check, banks in India normally extends the tenure of the loan to reduce the burden of the borrower. However, there is a limit to which the tenure may be increased to soften this impact. Banks and housing finance companies should therefore simultaneously monitor the movement of net credit exposure over time and its sensitivity with interest rate and house price movements as a mitigation tool against future risk of default.

Default chance is also lower when banks or lending institutions see a higher additional collateral (ADCOLLD dummy=1 if additional collateral is present and 0 otherwise with |z|=2.48 which means level of significance is 5 percent or better in Table 10) and it is highly positively significant). The presence of more number of co-borrowers (NO_CO_BORR) also significantly reduces the risk of default (Table 10). More importantly, higher the co-borrower's monthly income (COBOR_MINC), lesser is the chance of default because of availability of second line of source of income. It is interesting to note here that Indian banks & HFCs do prefer to include house-wife also as a co-borrower; this is with the view that a typical Indian house-wife would not like to default in housing loan, which is the dwelling house of the family.

As age increases and the number of dependents increases, risk of default also rises. Age dummies capture the differential impact of age factor on loan default. Borrowers in the age range of 50-60 (AGED3) are riskier than the borrowers at age group below 40 (AGED1), age range of 40-50 (AGED2), and above 60 (AGED4). Borrowers in the age group of below 40 (AGED1) are found to be the safest (comparing the coefficients).This may be explained by two factors:

1) Aggressive selling of personal loans (2004 onwards) by banks might have resulted in over-stretching the capabilities of the individuals who might have already availed-of

housing loans in this group and jeopardized their ability to service EMIs of housing loans; Moreover, being already in the higher age bracket they probably had lesser number of service years left and the lender had limited maneuverability to adjust the EMI over the remaining years of service to soften the impact of strained financial position;

2) Borrowers in the age group of below 40 years might have joined the loan stream in later years, and hence defaults in younger age group might show a better picture.

We have found that sub-urban and rural borrowers are significantly riskier than the urban borrowers, and semi urban borrowers are riskier than rural borrowers. (See the property location dummy effects with respect to the dummy that has been dropped). This perhaps captures the local situational factors on risk of default. To more accurately capture the effect locational factors on default risk, we have further re-grouped the 20 regional dummies into 3 city-size-wise dummies (CITYD1_BIG: big cities, CITYD2_MEDIUM: medium sized cities and CITYD3_SMALL: small cities) and tested their impact on loan default (Table 10 results). We find that borrowers located in than medium (CITYD2_MED: Ahmedabad, Chandigarh, Coimbatore, Hyderabad, Indore, Lucknow, Nagpur, Nashik, Pune and Vadodara) and smaller cities (CITYD3_SMALL: Bhubaneshwar, Guwahati, Trivandrum, Jaipur and Kochi) are safer than in big cities (like Bangalore, Mumbai, Kolkata, New Delhi and Chennai (CITYD1_BIG). This may be because with the activation of personal loan segment by commercial banks and easy access to such loans especially in the metro area prompted the existing home loan borrowers to overstretch their financial commitments with a consequential deleterious effect on home loan default rate in this segment.

The effect of employment on housing default has also been examined (represented by employment dummies). We find that employment (EMPD1_EMPLOYED) has significantly negative impact on default risk. Self employed borrowers (EMPD2_SELF_EMPLOYED) are quite risky probably due to absence of steady stream of income like the employed class.

***5.3. Important determinants of housing loan recovery***

Next, we have examined the contribution of various factors in housing loan recovery. For this, we have run a Tobit censored multivariate regression on loan recovery rate (RR) to investigate the various determinants of recovery. The loan recovery rate is the ratio of total recovery of the defaulted loan till the financial year 2006-07 divided by the amount outstanding at the date of default (EAD). We have used panel tobit regression method to ascertain the various factors (borrower/loan specific and other industry or economic /regional factors) play role in determining the probability that how much of the loan outstanding the bank will be able to recover from the defaulted amount. Censoring (at 0 level) the dependent variable is required to control the possibility of 0 or negative recovery which may bias the prediction (if not considered). Here, our objective was not only to predict whether there will be recovery or not but also to ascertain how much will be recovered from the defaulted outstanding (or call it exposure at default or EAD). A tobit exercise which performs maximum likelihood technique (MLE) provide more efficient and unbiased estimate than OLS.[4]

Our regression results reported in the Table 11 reveals some interesting facts. We have seen value of property or house as proportion to the original loan amount (SECVAL_LOANAMT) significantly and positively affects recovery. It means higher is the actual margin (calculated by bank) that the borrower is giving, better is the likelihood of

[4] See Greene, W. (1997). Econometric Analysis, 3rd Edition, Prentice Hall.

recovery on the loan. This confirms the importance of collateral valuation and factoring loan to value ratio (LTV) into risk analysis by the bank. A 10 percent increase in the ratio (secval_loanamt) lead to 0.21 percent increase in the recovery rate (RR). Moreover, due to the presence of guarantee, bank's likelihood of recovery is more (confirmed by the positive significance of GURANTD).

Higher loan to income ratio (LOAN_INCR) is the reflection of borrower's riskiness which has dampening impact on recovery prospect of the defaulted loan (confirmed by the significantly negative coefficient). In a separate regression, we have also tested affordability variable[5] on recovery rate and found that this ratio has also significantly negative impact on RR (results not reported in Table 11). It means that if property becomes un-affordable because of higher gap between its average value and borrower's average income, recovery chance from defaulted loans also suffer. Similarly, our regression results show that higher number of dependents significantly reduces the scope of recovery (negative sign of NO_DEPEND) due to higher financial burdens which is quite expected.

[Insert Table 11 here]

Interestingly, Age of the borrower is positively significant on recovery rate on the loan. The recovery rate is highest in the age slab of more than 60 groups. We have also found that housing loan recovery rate in urban and rural area is significantly higher than in the sub-urban area. The regional variations in recovery rates are being captured by city-wise regional location dummies. Medium and Smaller cities have higher recovery rates than the Big cities. Interestingly, recovery from retired & pensioners and self employed groups are significantly better than employed, self employed, unemployed and retired borrower counterparts.

[5] It is the ratio of book value of the property to gross annual income. We assume higher the ratio, lesser is the affordability of the borrower from its internal source of income and higher is the leverage factor.

## 6. Summary and Concluding Discussions

The primary contribution of the research delineated in this paper is to demonstrate the importance of borrower specific characteristics in determining the demand prospect as well as the risk of credit loss on residential housing loan repayment. Growing competition and reduction in regulatory risk weights on housing loans has provided a substantial incentive to the lending institutions in India resulting in aggressive practices including very high Loan to Value (LTV) loans, softening of collateral requirements, competitive pricing etc. However, we have learnt from the recent US mortgage crisis that many lenders, especially sub-prime lenders has been caught into the web of "boom time facile lending practices" of over-generosity to several borrowers with unpalatable credit histories and very low margin. This has led to current unforeseen and negative consequences of homeowners' inability to sustain mortgage payments resulting in numerous foreclosures and credit defaults. Understanding the interplay between various factors driving housing sector demand and their link with borrower default will no doubt help the policy planners, regulators and lenders.

Using 13,487 housing loan accounts (sanctioned from 1993-2007) data from Housing Finance Institutions (HFIs) in India we investigate the crucial factors that drive household demand for housing and the correlation of borrower characteristics with housing demand have been presented. We have observed that housing demand growth in India is mainly driven by accessibility and credit availability, changing income level, increasing GDP growth rate, changing family pattern and age demographic effect. An increase in house price by 10 percent, ceteris paribus, results in a 4.59 percent decrease in housing demand (in terms of floor area) as affordability comes down. A 10 percent increase in the monthly income of the borrower leads to increase in housing demand area by almost 6 percent.

Further, the demand for house-size is found to be inversely related with the age of the borrowers. The number of dependence, which capture the financial liability of the borrower, is found to have negatively significant implying thereby more the number of dependents in a family reduces the affordability and hence the size of the house. The study notes that demand for bigger house area (in square meter) is significantly higher in sub-urban and rural area than in urban areas. Citizens in smaller (tier III) and medium sized (tier II) cities have greater demand for bigger houses than population in big cities (metros).

Next, we examine housing loan defaults and the major causative factors. Our empirical results suggest that borrower defaults on housing loan payments is mainly driven by change in market value of the property vis-à-vis the loan amount and EMI to income ratio. A 10 percent decrease in the market value of the property vis-à-vis the loan amount raises the odds of default by 1.55 percent. Similarly, a 10 percent increase in EMI to income ratio raises the delinquency chance by 4.50 percent. This essentially means that volatility of potential credit exposure needs to be properly understood (especially in a rising rate environment and unstable market condition). We have empirically observed the influence of systematic factor on loan default rates: an increase in GDP growth rate significantly reduces the likelihood of default.

Ignoring borrower details like marital status, employment situation, regional locations, city locations, age profile, house are preference may inhibit the lender to properly assess the credit risk in home loan business, as our study suggests, these parameters also act as default triggers. We found that default is lower in cases where the house is larger in size, the monthly income is higher, asset value is higher and age of the borrower is lower. The presence of more number of co-borrowers and their income level significantly reduces the risk of default. It has been found that sub-urban and rural borrowers are significantly riskier than the urban borrowers, and semi urban borrowers are riskier than rural borrowers. However, metro dwellers are riskier than those living in Tier II and III towns. This could be because people living in metros have access to easy loans from commercial banks, leading to the borrower being over stretched. Employment has significantly risk reduction effect; we find higher default percentage in self employed people.

We have also studied the key factors driving the recovery prospect in the housing loan segment. Our Tobit censored multivariate regression results suggests that higher is the actual margin better is the likelihood of recovery on the loan. This confirms the importance of collateral valuation and factoring loan to value ratio (LTV) into risk analysis by the bank. Presence of guarantee is found [to found] to improve bank's likelihood of recovery. A 10 percent increase in the ratio (SECVAL_LOANAMT) lead to 0.21 percent increase in the recovery rate (RR). However, higher number of dependents significantly reduces the scope of recovery. We have found that housing loan recovery rate in urban and rural area is significantly higher than in the sub-urban area. Medium and Smaller cities have higher recovery rates than the Big cities. Interestingly, recovery from retired & pensioners and self employed groups are significantly better than employed, self employed, unemployed and retired borrower counterparts.

**Reference**


Amemiya, T. (1981). Tobit models: A survey. *Journal of Econometrics,* 24, 3-61.

Arimah, B. C. (1997). The determinants of housing tenure choice in Ibadan, Nigeria. *Urban Studies*, *34(1),* 105-124.

Bajari, P., & Kahn, M. E. (2003). Estimating housing demand with an application to explaining racial segregation in cities. NBER Working Paper No. 9891.

Baku, E., & Smith, M. (1998). Loan delinquency in the community lending organizations: Case studies of neighbor Works Organizations. *Housing Policy Debate 9,* 151-175.

Bartik, T. J. (1987). Estimating hedonic demand parameters with single market data: The problems caused by unobserved tastes. *The Review of Economics and Statistics 69(1)*, 178-80, February.

Brown, J. N., & Rosen, H. S. (1982). On the estimation of structural hedonic price models. *Econometrica 50(3),* 765-768.

Calem, P., & Wachter, S. (1999). Community reinvestment and credit Risk: Evidence from affordable-home- loan program. *Real Estate Economics 27,* 105-134.

Campbell, T. S., & Dietrich, J. K. (1984). The determinants of default on insured conventional residential mortgage loans. *The Journal of Finance 38 (5),* 1569-1581.

Canner, G. B., Gabriel, S. A., & Woolley, J. M. (1991). Race, default risk and mortgage lending: A study of the FHA and conventional loan markets. *Southern Economic Journal, 58(1),* 249-262.

Chinloy, P. (1995). Privatized default risk and real estate recessions: The U.K. mortgage market. *Real Estate Economics 23 (4),* 410-420.

Deng, Y., Quigley, J. M., & Order, R. V. (1995). Mortgage default and low downpayment loans: The cost of public subsidy, NBER Working Paper no. 5184.

Ellis, L. (2008). The housing meltdown: Why did it happen in the United States? BIS Working Paper no. 259.

Epple, D. (1987). Hedonic prices and implicit markets: Estimating demand and supply functions for differentiated products. *Journal of Political Economy 95 (1),* 59-80.

Follian, J., W., Huang, V., & Ondrich, J. (1999). Stay, pay or walk away: A hazard rate analysis of FHA-insured mortgage terminations, Draft paper, Freddie Mac and University of Syracuse.

Furstenberg, G. V., & Green, R. (1974). Estimation of delinquency risk for home mortgage portfolios. A*REUEA Journal* 2, 5-19.

Gerardi, K., Lehnert, A., Sherlund, S., & Willen, P. (2008). Making sense of the subprime crisis. Brooking Papers on Economic Activity, Fall.

Getter, D. (2003). Contributing to the delinquency of borrowers. *The Journal of Consumer Affairs 37,* 86-100.

Ingram, F. J., & Frazier, E. L. (1982). Alternative multivariate tests in limited dependent variable models: An empirical assessment, *Journal of Financial and Quantitative Analysis 17 (2),* 227-240.

Kau, J., & Keenan, D. (1998). Patterns of rational default, Working Paper, University of Georgia.

Kiff, J., & Mills, P. (2007). Money for nothing and checks for free: recent developments in U.S. subprime mortgage markets. IMF Working Paper no 07/188.

Lawrence E. C., & Arshadi, N. (1995). A multinomial logit analysis of problem loan resolution choices in banking. *Journal of Money, Credit and Banking 27 (1),* 202-216.

Lawrence, E. C., & Smith, L. D. (1992). An analysis of default risk in mobile home credit. *Journal of Banking and Finance 16,* 299-312.

Lee, S. P. (2002). Determinants of default in residential mortgage payments: A statistical analysis, *International Journal of Management*, June.

Madalla, G. S. (1983). Limited Dependent and Qualitative Variables in Econometrics. New York: Cambridge University Press.

Mills, E. S., & Lubuele, L. S. (1994). Performance of residential mortgages in low and moderate-income neighborhoods. *Journal of Real Estate Finance and Economics 9 (3),* 245-260.

Morton, T. (1975). A discriminant function analysis of residential mortgage delinquency and foreclosure. *AREUEA Journal 3,* 73-90.

Reddy, Y. V. (2005). Midterm Review of Annual Policy Statement for the Year 2005-06. Reserve Bank of India.

Reddy, Y. V. (2006). Annual Policy Statement for the Year 2006-07. Reserve Bank of India.

Riddiough, T. J. (1991). Equilibrium Mortgage Default Pricing with Non-Optimal Borrower Behavior, University of Wisconsin Ph.D. diss.

Rosen, S. (1974). Hedonic prices and implicit markets: Product differentiation in pure competition. *Journal of Political Economy82 (January/February),* 34-55.

Rosengren, E. S. (2008). Current challenges in housing and home loans: Complicating factors and the implications for policymakers. Conference Paper, Boston, Massachusetts.

Stansell, S. R., & Millar, J. A. (1976). An empirical study of mortgage payment to income ratios in a variable rate mortgage program. *The Journal of Finance 31 (2),* 415-425.

Tsatsaronis, K., & Zhu, H. (2004).What drives housing price dynamics: cross-country evidence. *BIS Quarterly Review, March,* 65-78.

Vandell, K. D. (1978). Default risk under alternative mortgage instruments, *The Journal of Finance 33 (5),* 1279-1296.

Vandell, K. D., Thibodeau, T. (1985). Estimation of mortgage defaults using disaggregate loan history data. *AREUEA Journal 15 (3),* 292-317.

Vandell, K., Barnes, W., Hartzell, D., Kraft, D., & Wendt, W. (1993).Commercial mortgage defaults: Proportional hazards estimation using individual loan histories. *Journal of the American Real Estate and Urban Economics Association 21 (4),* 451-80.

Waller N. G. (1988). Residential mortgage default: A clarifying analysis. *Housing Finance Review 7,* 321-333.

Webb, B. G. (1982). Borrower risk under alternative mortgage instruments. *The Journal of Finance.37 (1),* 169-183.

Wiliams, A. O., Beranek W., & Kenkel, J. (1974). Default risk in urban mortgages: A Pittsburgh prototype analysis. *American Real Estate and Urban Economics Association Journal 2,* 101-112.

**Table 1**
**Housing Finance Disbursement by various Institutions**

**(Units in Rs. Crore)**

| Institutions | 2000-01 | 2001-02 | 2002-03 | 2003-04 | 2004-05 | 2005-06 | 2006-07 |
|---|---|---|---|---|---|---|---|
| All Scheduled Commercial Banks (PSBs) | 25412.41 | 32825.92 | 49066.92 | 85346.45 | 126797.03 | 182167.2 | 230689 |
| Housing Finance Companies (HFCs) | 12638 | 14614.44 | 17832.01 | 20862.23 | 26000 | 29500 | 32500 |
| Total | 38050.41 | 47440.36 | 66898.93 | 106208.7 | 152797.03 | 211667.2 | 263189 |
| % Share of HFCs | 33.21% | 30.81% | 26.66% | 19.64% | 17.02% | 13.94% | 12.35% |
| Total YoY Growth (%) | 29% | 22% | 34% | 46% | 36% | 33% | 22% |

Source: Basic Statistical Returns of RBI & various NHB Reports

**Table 2:**
**Deployment of Gross Bank Credit in Real Estate and Housing Segment**

**(Rs. Crore)**

| Outstanding as On | March 23, 2001 | March 22, 2002 | March 21, 2003 | March 19, 2004 | March 18, 2005 | March 31, 2006 | March 30, 2007 |
|---|---|---|---|---|---|---|---|
| Gross Bank Credit | 469153 | 536727 | 669534 | 764383 | 972587 | 1443920 | 1841878 |
| Food Credit | 3991 | 53978 | 49479 | 35961 | 41121 | 40691 | 46521 |
| Non-Food Gross Bank Credit (1 to 4) | 429162 | 482749 | 620055 | 728422 | 931466 | 1403229 | 1795357 |
| Real Estate Loans | 1766 | 2596 | 5894 | 5577 | 10612 | 26693 | 45328 |
| Share in total non-food bank credit (%) | 0.41% | 0.54% | 0.95% | 0.77% | 1.14% | 1.90% | 2.52% |
| Housing Loans | 16143 | 22346 | 36587 | 51981 | 75173 | 185181 | 230689 |
| Share in total non-food bank credit (%) | 3.76% | 4.63% | 5.90% | 7.14% | 8.07% | 13.20% | 12.85% |
| Incremental Share | | 20.8% | 24.2% | 19.1% | 12.2% | 49.2% | -2.7% |

Note: Gross Bank Credit=Food Credit+Non food credit
Source: RBI Trends and Progress

**Table 3: Projection of housing demand through credit supply**

| (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|
| **Year** | **No. of Loans disbursed by PSBs** | **Share of HFCs** | **No. of Loans disbursed by HFCs** | **Total no. of Housing Loans** | **Households Number (million)** | **Loan No./HH no.** |
| 1994-95 | 819856 | 40% | 327942 | 1147798 | 167.84 | 0.68% |
| 1995-96 | 1033802 | 40% | 413521 | 1447323 | 171.14 | 0.85% |
| 1996-97 | 1080164 | 40% | 432066 | 1512230 | 174.51 | 0.87% |
| 1997-98 | 1275149 | 40% | 510060 | 1785209 | 177.95 | 1.00% |
| 1998-99 | 2253390 | 41% | 923890 | 3177280 | 181.46 | 1.75% |
| 1999-00 | 2482797 | 37% | 918635 | 3401432 | 185.04 | 1.84% |
| 2000-01 | 1816315 | 25% | 454079 | 2270394 | 188.70 | 1.20% |
| 2001-02 | 2446081 | 30% | 733824 | 3179905 | 191.96 | 1.66% |
| 2002-03 | 3035026 | 23% | 698056 | 3733082 | 197.09 | 1.89% |
| 2003-04 | 3326452 | 19% | 632026 | 3958478 | 202.00 | 1.96% |
| 2004-05 | 3666450 | 15% | 549968 | 4216418 | 207.07 | 2.04% |
| 2005-06 | 4521531 | 12% | 542584 | 5064115 | 212.31 | 2.39% |

**Table 4**
**Potential Demand For Housing: Projected Scenarios**

| Year | Loan Growth @ 2.35% | Loan Growth @ 2.50% | Loan Growth @ 3.30% |
|---|---|---|---|
| 2006-07 | 5.12 | 5.44 | 6.53 |
| 2007-08 | 5.25 | 5.58 | 6.70 |
| 2008-09 | 5.38 | 5.73 | 6.87 |
| 2009-10 | 5.52 | 5.88 | 7.05 |
| 2010-11 | 5.67 | 6.03 | 7.23 |
| 2011-12 | 5.82 | 6.19 | 7.43 |

The above figures are in million units
Loan growth rate (%): Number of housing loan/Households number

**Figure1: The link between Housing Loan Growth and GDP Growth**

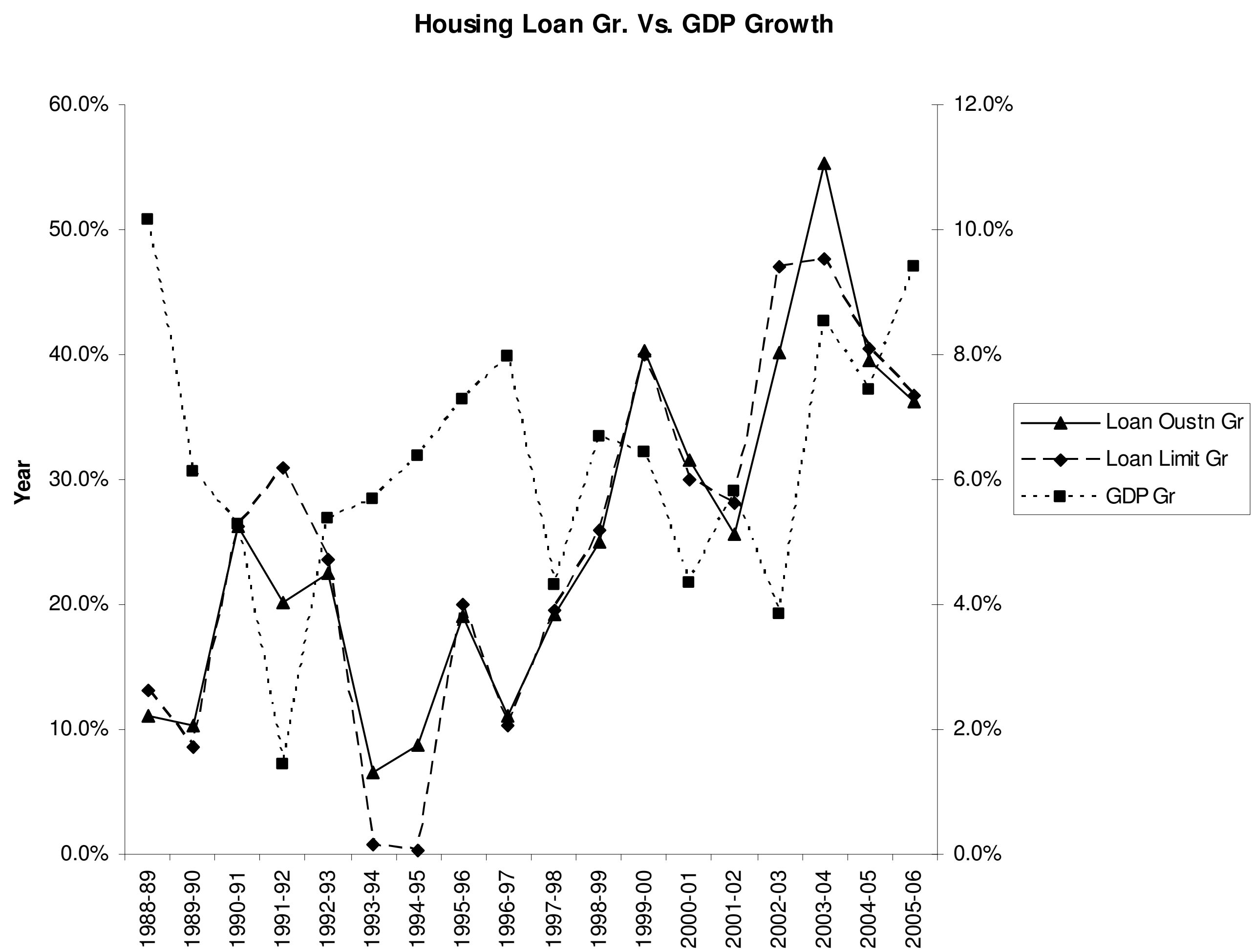
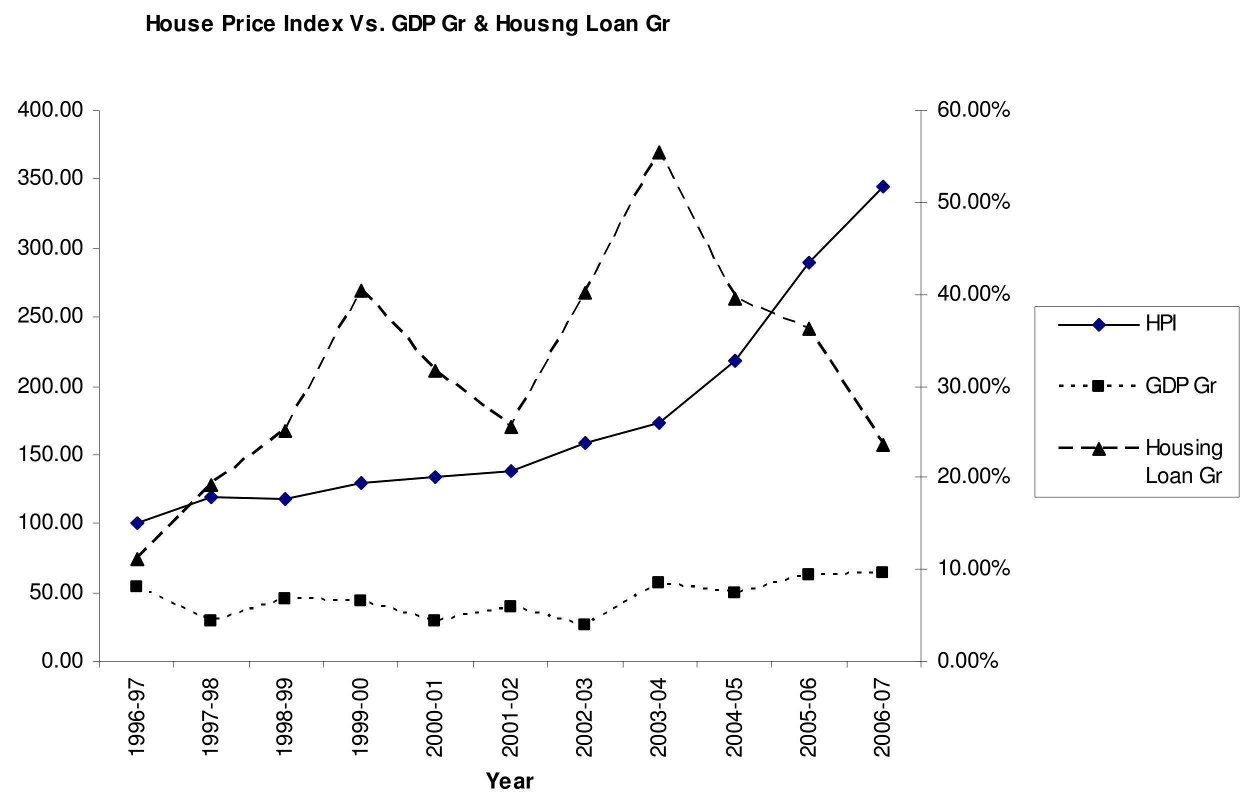


**Figure 2: House Price Movement with Economic Growth & House Loan Growth**




Note: The house price index is computed on the basis of housing loan data of a leading HFC using Laspeyres index by taking 1997 as the base (=100). The house price is the property price per square meter. The weights are the property area in terms of square meter. The bank's housing loan growth (annual) is computed based on the data obtained from BSR statistics.

**Table 5:**
**Variable definitions**

| Variable | Definition |
|---|---|
| LNAREA_HD | Natural log of area of House (in square meter) : Dependent variable measures housing demand in section III.2 exercise |
| DDEF | Dummy (0/1) variable=1 if account is NPA and 0 if account is in standard category: Dependent variable in section III.3 exercise |
| RR | Recovery rate is calculated as the total amounts recovered till 2006-07 in comparison with the outstanding amount on the date of default: Dependent variable in section III.4 exercise |
| LN_MINC | Natural log of monthly income of the borrowers [=ln(monthly income)] |
| LHOUSEPR_SQM | Natural log of house price per square meter [=ln(book value of property/property area in square meter] |
| NO_DEPEND | Number of dependents in the borrower's family |
| PROPLOCND1_URBAN, PROPLOCND2_SUB-URBAN and PROPLOCND3_RURAL | Three property location dummies (0/1) variable (represent location of the property) =1 if the borrower is located either in Urban/Sub-urban/Rural, otherwise 0. |
| SECVAL_LOANAMT | The ratio of Original book value of the property at the time of sanction (or property cost) over original loan amount capture the original security margin available for the loan |
| GURANTD | Dummy (0/1) variable=1 if third party guarantee is present |
| ADCOLLD | Dummy (0/1) variable =1 if additional collateral is present and =0 otherwise |
| NO_CO_BORR | Number of co-borrowers present |
| COBOR_MINC | Co-borrower's monthly income |
| EMPD1_EMPLOYED, EMPD2_SELF-EMPLOYED, EMPD3_Unemployed & HOUSE WIVES and EMPD4_RETIRED_&_PENSIONER | Set of four employment dummy(0/1) variable depending upon employment types |
| GDPGR | GDP growth rate during the year of loan sanction |
| ORGNL_TERMM | Original tenure of the loan (in months) |
| AGE_BORR | Age of the borrower |
| AGED1_<40, AGED2_40-50, AGED3_50-60 and AGED4_>60 | Set of four dummy (0/1) variable classifying borrowers/individuals by respective age groups |

| | |
|---|---|
| SURVIVAL_DAYS | Number of days of survival of loan from the origination day. For defaulted loan: days between granting of loan and default. For good loans or standard accounts, days between granting and latest reporting year (31st March, 2007 |
| CITYD1_BIG | Dummy (0/1) variable =1 if borrower is located in big cities like Bangalore, Mumbai, Kolkata, New Delhi and Chennai and =0 otherwise |
| CITYD2_MEDIUM | Dummy (0/1) variable =1 if borrower is located in medium sized cities like Ahmedabad, Chandigarh, Coimbatore, Hyderabad, Indore, Lucknow, Nagpur, Nashik, Pune and Vadodara and =0 otherwise |
| CITYD3_SMALL | Dummy (0/1) variable =1 if borrower is located in medium sized cities like Bhubaneshwar, Guwahati, Trivandrum, Jaipur and Kochi and =0 otherwise |
| LOAN_INCR | Loan amount to gross annual income ratio of the borrower |
| EMI_INCR | EMI to Monthly income ratio of the borrower |
| LN_ASSTVAL | Natural log of asset value of the borrower |

**Table 6:**
**Overall Sample descriptive statistics**

| Variable | Mean | S.D | Median | 25% | 75% | Kurtosis |
|---|---|---|---|---|---|---|
| GROSS MONTHLY INCOME (RS.) ('000) | 15.54 | 22.38 | 9.84 | 7.088 | 15.487 | 133.89 |
| PROPERTY AREA (SQ. METER) | 85.36 | 88.47 | 70 | 50 | 100 | 579.50 |
| AGE_BORR | 43.59 | 8.34 | 44 | 38 | 50 | 2.616 |
| NO_DEPEND | 1.58 | 1.38 | 2 | 0 | 3 | 0.535 |
| PROPLOCND1_URBAN | 0.7414 | 0.44 | 1 | 0 | 1 | 2.22 |
| PROPLOCND2_SUB-URBAN | 0.0352 | 0.184 | 0 | 0 | 0 | 26.44 |
| PROPLOCND3_RURAL | 0.223 | 0.42 | 0 | 0 | 0 | 2.76 |
| CITYD1_BIG | 0.3349 | 0.472 | 0 | 0 | 1 | 1.49 |
| CITYD2_MEDIUM | 0.5041 | 0.50 | 1 | 0 | 1 | 1 |
| CITYD3_SMALL | 0.161 | 0.367 | 0 | 0 | 0 | 4.41 |
| EMPD1_EMPLOYED | 0.9040 | 0.294 | 1 | 1 | 1 | 8.59 |
| EMPD2_SELF-EMPLOYED | 0.067 | 0.25 | 0 | 0 | 0 | 13.03 |
| EMPD3_Unemployed & HOUSE WIVES | 0.024 | 0.152 | 0 | 0 | 0 | 40.41 |
| EMPD4_RETIRED_&_PENSIONER | 0.005 | 0.07 | 0 | 0 | 0 | 199.17 |
| AGED1_<40 | 0.3301 | 0.47 | 0 | 0 | 1 | 1.52 |
| AGED2_40-50 | 0.4108 | 0.49 | 0 | 0 | 1 | 1.13 |
| AGED3_50-60 | 0.2387 | 0.426 | 0 | 0 | 0 | 2.50 |
| AGED4_>60 | 0.0202 | 0.141 | 0 | 0 | 0 | 47.42 |

**Table 7:**

**Year-wise Age Pattern of House Loan Demand**

| **Observations** | **Mean** | **Std. Dev.** | **Year** | **T statistics for difference** |
|---|---|---|---|---|
| 1177 | 46.28 | 7.26 | 2000 | |
| 1417 | 45.55 | 7.48 | 2001 | -2.52** |
| 1968 | 44.75 | 7.60 | 2002 | -3.04** |
| 1578 | 44.08 | 7.70 | 2003 | -2.61** |
| 1707 | 42.93 | 7.90 | 2004 | -4.22** |
| 1165 | 41.70 | 7.90 | 2005 | -4.09** |
| 1912 | 38.73 | 8.36 | 2006 | -9.74** |
| 732 | 38.49 | 9.16 | 2007 | -0.64 |

Note: ** denotes significance at 5% or better level

**Table 8:**

**Comparison between Solvent and Defaulted Home Loan Borrowers**

| Variable Name | Mean | | | Std. Dev. | |
|---|---|---|---|---|---|
| | **Solvent** | **Defaulted** | **t-test for Difference[$]** | **Solvent** | **Defaulted** |
| PROPERTY AREA (SQ. METER) | 101.67 | 65.99 | 35.68** (23.81) | 114.89 | 27.50 |
| LNAREA_HD | 4.42 | 4.10 | 0.317** (35.82) | 0.578 | 0.421 |
| GROSS MONTHLY INCOME (RS.) | 20,443.30 | 9,711.90 | 10,731.40** (28.56) | 28891.63 | 6501.132 |
| LN_MINC | 9.55 | 9.06 | 0.484** (43.56) | 0.768 | 0.449 |
| LHOUSEPR_SQM | 8.92 | 8.68 | 0.2458** (23.52) | 0.692 | 0.481 |
| AGE_BORR | 42.79 | 44.58 | -1.79** (-12.42) | 8.84 | 7.70 |
| NO_DEPEND | 1.445 | 1.744 | -0.2988** (-12.57) | 1.343 | 1.411 |
| LN_ASSTVAL | 12.75 | 11.95 | 0.798** (22.15) | 1.452 | 1.271 |
| SECVAL_LOANAMT | 1.65 | 1.499 | 0.15** (10.05) | 0.987 | 0.69 |
| NO_CO_BORR | 0.48 | 0.31 | 0.174** (18.70) | 0.57 | 0.50 |
| COBOR_MINC | 3061.04 | 1024.64 | 2036.4** (12.30) | 12715.4 | 2940.8 |
| ORGNL_TERMM | 173.26 | 176.4 | -3.14** (-3.8) | 48.03 | 47.60 |
| SURVIVAL_DAYS | 1367.34 | 204.21 | 1163.13** (44.73) | 2030.78 | 223.77 |
| No. of observations | 7321 | 6166 | | | |

Note:
$ Outcome of an un-paired t-test for the difference in mean
Figures in the parentheses are the t values
** denotes significance at 5% or better

It is important to note that we have found average survival period for defaulted loans is approximately 204 days

**Table 9**

**The determinants of Housing Demand:** Panel least square dummy variable regression with robust standard errors on natural logarithm of house area (dependent variable: LNAREA_HD )

| Independent variables | Coefficient estimate | T-statistic |
|---|---|---|
| LN_MINC | 0.599 | 61.57** |
| LHOUSEPR_SQM | -0.459 | -33.52** |
| NO_DEPEND | -0.015 | -5.87** |
| PROPLOCND1_URBAN | dropped | |
| PROPLOCND2_SUB-URBAN | 0.107 | 5.67** |
| PROPLOCND3_RURAL | 0.02 | 2.32** |
| CITYD1_BIG | dropped | |
| CITYD2_MEDIUM | 0.018 | 2.02* |
| CITYD3_SMALL | 0.240 | 18.63** |
| AGED1_<40 | 0.067 | 6.56** |
| AGED2_40-50 | 0.048 | 5.23** |
| AGED3_50-60 | dropped | |
| AGED4_>60 | 0.069 | 2.04** |
| EMPD1_EMPLOYED | -0.162 | -2.42** |
| EMPD2_SELF-EMPLOYED | 0.171 | 2.46** |
| EMPD3_Unemployed & HOUSE WIVES | -0.120 | -1.69* |
| EMPD4_RETIRED_&_PENSIONER | dropped | |
| INTERCEPT | 3.142 | 31.38** |
| | | |
| Number of observations | 12423 | |
| Model R2 | 0.465 | |

Note:

** Significant at 5% or better

* Significant at 5-10%.

**Table 10**
**Factors determine housing loan default:** Logit regression results (dependent variable: DDEF)

| Independent variables | Coefficient estimate | Z-statistic |
|---|---|---|
| LNAREA_HD | -0.982 | -21.64** |
| EMI_INCR | 0.371 | 2.69** |
| SECVAL_LOANAMT | -0.169 | -5.64** |
| GDPGR | -13.879 | -12.86** |
| NO_DEPEND | 0.058 | 3.89** |
| ADCOLLD | -0.145 | -2.48** |
| NO_CO_BORR | -0.244 | -5.67** |
| COBOR_MINC | 0.000 | -7.74** |
| ORGNL_TERMM | 0.007 | 12.21** |
| PROPLOCND1_URBAN | dropped | |
| PROPLOCND2_SUB-URBAN | 0.622 | 5.80** |
| PROPLOCND3_RURAL | 0.579 | 11.71** |
| CITYD1_BIG | dropped | |
| CITYD2_MEDIUM | -0.136 | -3.06** |
| CITYD3_SMALL | -0.534 | -7.99** |
| AGED1_<40 | -0.866 | -13.02** |
| AGED2_40-50 | -0.429 | -7.53** |
| AGED3_50-60 | dropped | |
| AGED4_>60 | -0.228 | -1.47 |
| EMPD1_EMPLOYED | -0.362 | -2.71** |
| EMPD2_SELF-EMPLOYED | 0.495 | 3.18** |
| EMPD3_Unemployed & HOUSE WIVES | dropped | |
| EMPD4_RETIRED_&_PENSIONER | -0.228 | -1.47 |
| INTERCEPT | 5.395 | 21.71** |
| Number of observations | 12407 | |
| LR $Chi^2$ statistic (degrees of freedom) | 2185.75 (19) | |
| Prob>$Chi^2$ | 0.00 | |
| Pseudo $R^2$ | 0.13 | |

Note:
The dummies are dropped due to collinearity
** Significant at 5% or better
* Significant at 5-10%.

**Table 11**
**Factors determine housing loan recovery rate:** Tobit regression results (dependent variable: RR)

| **Independent variables** | **Coefficient estimate** | **T-statistic** |
|---|---|---|
| LOAN_INCR | -0.046 | -20.66** |
| SECVAL_LOANAMT | 0.021 | 5.87** |
| NO_DEPEND | 0.004 | 2.2** |
| GURANTD | 0.053 | 9.7** |
| PROPLOCND1_URBAN | 0.046 | 3.90** |
| PROPLOCND2_SUB-URBAN | dropped | |
| PROPLOCND3_RURAL | 0.063 | 5.16** |
| CITYD1_BIG | dropped | |
| CITYD2_MEDIUM | 0.037 | 7.27** |
| CITYD3_SMALL | 0.027 | 3.04** |
| AGED1_<40 | -0.141 | -21.4** |
| AGED2_40-50 | -0.130 | -22.42** |
| AGED3_50-60 | dropped | |
| AGED4_>60 | 0.256 | 13.25** |
| EMPD2_SELF-EMPLOYED | 0.053 | 5.83** |
| EMPD4_RETIRED_&_PENSIONER | 0.077 | 1.85* |
| INTERCEPT | 0.337 | 27.19** |
| | | |
| Number of observations | 5856 | |
| LR $Chi^2$ statistic (degrees of freedom) | 2019.88 (13) | |
| $Prob>Chi^2$ | 0.00 | |
| Pseudo $R^2$ | 0.101 | |

Note:
The dependent variable is amount recovered to total loan outstanding at the time of default and is left censored at zero.
The dummies are dropped due to collinearity

** Significant at 5% or better
* Significant at 5-10%.