Mortgage Prepayment Behavior in a Market with ARMs only

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A study on the prepayment behavior of Hong Kong mortgage loans is conducted. With all of the loans as adjustable-rate mortgages (ARMs), we find that 1) Prepayment speeds up and then slows down as the mortgage seasons; 2) Prepayment speeds up as the rate markup decreases; 3) Prepayment speeds up as the interest rate increases; 4) Prepayment speeds up when the profitability ratio of the banks (the prime-HIBOR spread) is higher; 5) Prepayment speeds up as the price of the property market falls; 6) Prepayment speed is faster for loans with a lower loan-to-value ratio; 7) Prepayment exhibits a seasonal pattern: people tend to prepay in the summer.

Keywords

1.   Introduction

With a rising property market over the past many years, a major portion of commercial banks' assets in Hong Kong is now composed of residential mortgage loans. Any strong movement in the property market or interest rates could prove damaging, and this poses a great risk to the commercial banks and to the health of the financial system as a whole. A more active secondary market on mortgage loans, and even a government sponsored mortgage corporation, are now emerging to answer the need of institutional

investors to diversify their risk.   To facilitate trading in this market, it is essential, given Hong Kong's unique risk environment and geographic identity, to understand the characteristics of the mortgage loans.

Borrowers have the right to pay off all or just a part of the mortgage balance at any time subject to penalties. This uncertainty leads to a prepayment risk for the lenders. A study of the prepayment behavior and the corresponding risk thus becomes a prerequisite for a sound risk management practice for any investor holding portfolios of mortgage loans. While there has been research into the prepayment behavior on the U.S. market, an investor, who is interested in investing in the secondary market of mortgage loans in Hong Kong, would want to know the prepayment pattern in Hong Kong. The research efforts focused on the Hong Kong mortgage loan market would be of special value given that there are some unique geographic and economic elements in Hong Kong.

While most of the previous mortgage prepayment studies have dealt with fixed-rate mortgage loans or had to incorporate the dimension caused by prepayment due to the switch from ARMs to fixed-rate mortgages, the scarcity of fixed rate mortgage loans in Hong Kong makes the current study more focused. Given that most mortgage loans in Hong Kong are plain vanilla type ARMs, mortgagors in Hong Kong do not have to consider the effects of interest rate caps/floors/teasor when they choose the mortgage. The prepayment behavior of ARMs in Hong Kong is thus probably more uniform since there are fewer factors affecting prepayment.

Mortgages can be thought of as a simple coupon bond plus a prepayment option.[1] The option can be exercised involuntarily or due to strong economic reasons. In this study, we try to capture some of the factors affecting mortgage prepayment behavior quantitatively. Among them, seasoning effect, financial reasons due to the sharpening of the rate markup, movements of the prime-HIBOR spread and the local property market, the individual loan characteristics and the summer effect.

The remainder of the paper is structured as follows.   In section 2, we introduce our econometrics model.   A proportional hazard model, which nicely separates the seasoning part from the effects of other economics factors, is used in our study. In section 3, we present the data the estimation results. A brief discussion of the empirical results is also included. Section 4 concludes.

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[1] We will omit the default option here.

2.   Econometric Model

The major components of residential mortgage loan prepayment are housing turnover, loan refinancing, partial prepayment and mortgage defaults. In turn, for an adjustable rate mortgage, non-economic reasons aside, the decision on when to exercise the prepayment option will be determined by factors relating to the above components as well as the ordinary factors as implicit in the seasoning effect and potential signaling effects similar to those suggested in Dunn and Spatt (1985). With partial prepayments being uncommon and defaults in residential mortgage loans rarely observed in Hong Kong, we will first try to locate the factors relating to the housing turnover and loan refinancing.

Hong Kong had a rising and volatile housing market for decades. Speculation in the housing market is prevalent. This leads to a great deal of housing turnover. Also due to the uncertainties in the political scene and the settling down of these uncertainties, there is a substantial immigration and emigration occurring, which again causes some housing turnover. The normal reasons for housing turnover also exist here. People shuffle (upgrade/downgrade) their housing portfolio from time to time because of changes in their income status. All these critically depend on the movements of the housing market which, in turn, are driven by the housing price variations and the term structure variations of the interest rates.

The adjustable-rate mortgage loans are charged as a markup on top of the prime rate.[2] The prepayment behavior in the case of ARMs would be less sensitive to the interest rate movements than in the case of fixed-rate mortgage loans. While the prepayment behavior in the ARMs case could be fairly interest rate insensitive, it is affected by the markup changes in the Hong Kong mortgage loans. Due to the boom of the local property market as well as the fierce competition between local banks to give loans, the interest rate markup has been decreasing from 225 basis points to the current 50 basis points. This drastic change happened in a short period of less than three years (1994~1997) and could induce a large incentive for mortgagors to refinance their mortgage loans. Thus mortgage prepayment due to mortgage refinancing is another major source of prepayment in Hong Kong.

While in-depth research would involve the modeling of the housing turnovers and refinancing of the loans at the micro-level, or the so-called

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[2] In Hong Kong, the prime rate is the rate banks charge to their most creditworthy customers.

structural modeling approach, in this research, instead, we will do a reduced form study as in the study of Schwartz and Toros (1989) and the Prudential Securities prepayment model as in Huang and Xia (1996). In other words, we will use a statistics model to summarize the patterns of the observed prepayment and the factors associated in a data set of the Hong Kong mortgage loans.

We will empirically model the prepayment function by the prepayment function. The prepayment function gives the probability of a mortgagor prepaying a mortgage during a particular period, conditional on the mortgage not having been prepaid prior to that period. By expressing this conditional probability as a function of various explanatory variables or covariates, we may assess statistically the significance of these covariates in influencing a mortgagor's prepayment decision.

Let T be a continuous random variable representing the time until prepayment of a mortgage, and let t denote its realization. Let $\underline{v} = (v_1, v_2, \ldots, v_3)$ be a vector of explanatory variables or covariates upon which the time until prepayment may depend, while $\underline{\theta} = (\theta_1, \theta_2, \ldots, \theta_3)$ is a vector of parameters to be estimated. The prepayment function $\pi(t;\underline{v}, \underline{\theta})$ is defined by

$$p(t;\underline{v},\underline{q}) = \frac{f(t;\underline{n},\underline{q})}{S(t;\underline{n},\underline{q})} \tag{1}$$

where $S(t;\underline{v},\underline{\theta})$ represents the survivor function. The prepayment function $\pi(t;\underline{v},\underline{\theta})$ specifies the instantaneous rate of prepayment at $T = t$, conditional upon the mortgage not having been prepaid prior to time t.

We model the prepayment function by a proportional-hazards model:

$$p(t;\underline{v},\underline{q}) = p_0(t;\underline{g},\underline{r})\exp(\underline{b}\underline{n}) \tag{2}$$

where the base-line hazard function $\pi_0(t;\underline{v}, \underline{\theta})$ is given by the log-logistic hazard function

$$p_0(t;\underline{g},\underline{r}) = \frac{\underline{g}\underline{r}(\underline{g})^{p-1}}{1+(\underline{g}t)^p} \tag{3}$$

The base-line hazard function measures the probability of prepayment under homogenous conditions, $\underline{v} = \underline{0}$. The log-logistic hazard function admits a variety of relationships between the probability of prepayment and the age of

the mortgage. In particular, for $p > 1$, the probability of prepayment increases from zero to a maximum at

$$t^* = (p-1)^{1/p} / \boldsymbol{g} \tag{4}$$

and decreases to zero thereafter. This kind of prepayment behavior is consistent with the seasoning effects. On the one hand, people tend not to prepay too soon after paying hefty setup costs; on the other hand, as time goes by, most prepayments would already have been made and the prepayment would slow down. By modeling the base-line hazard function, as opposed to employing an arbitrary specification, we incorporate our prior knowledge of seasoning's influence on mortgage prepayments.

The probability of prepayment does not depend solely upon the age of a mortgage. Our prepayment function takes into account the fact that various explanatory variables, $\underline{v}$, influence the prepayment decision. According to the proportional-hazards model, these explanatory variables have an equiproportional impact at all mortgage ages. The vector of regression coefficients, $\underline{\beta}(\beta_1, \beta_2,..., \beta_3)$, measures the effect of the covariates upon the prepayment decision.

To empirically implement our prepayment function requires that we specify explicitly the covariates influencing the mortgagor's prepayment decision. Given the lack of demographic information and the small size of Hong Kong, we will exclude the use of demographic or geographic explanatory variables in our analysis.

A mortgagor's prepayment decision is dependent upon the change of the interest rate markup on which the monthly installment is determined. We calculate the ongoing rate according to the average rate of the newly originated loan, $r_{ft} \cdot r_{ft}$ would contain information regarding the markup change as well as the interest rate movement. To investigate the effect of markup rises (falls) on the mortgagor's prepayment decision, we employ the covariate $v_1(t)$, where

$$v_1(t) = r_{ft} - r_{ct} \tag{5}$$

where r_{ct} denotes the rate the homeowner is currently paying. v_1 will give us a measure as to how large the markup reduction is or how large the benefit is to refinance. If $\beta_1 < 0$, the larger the markup reduction v_1 is, the higher is the speed of prepayment. Note here, the rate r_{ft} gives the markup charge to an average customer and r_{ct} may contain a premium or discount according to the creditworthy of the particular customer.

To allow for the possibility that prepayments may further accelerate when future rates are sufficiently lower than the current mortgage rate, we also consider the covariate:

$$v_2(t) = (r_{ft} - r_{ct})^3 \qquad\qquad (6)$$

The further acceleration in prepayments reflects transaction costs which make prepayment less profitable when interest cost savings are small. This covariate allows for the possibility that, for a sufficiently low rate difference, the resultant prepayment speed may be lower than the prepayment speed predicted by v_1 only. Here, we expect $\beta_2 > 0$.

A mortgagor's prepayment decision would depend on the level change of the interest rate term structure. When the prime rate increases, the cost of capital for the mortgagor also increases. The increase of cost of capital would then in turn reduce the incentive for the mortgagor to hold the mortgage and thus speed up prepayment. That is, if

$$v_3(t) = Prime\ Rate_{t-1} - Prime\ Rate_{t-2} \qquad\qquad (7)$$

we would expect $\beta_3 > 0$. Notice here we use the lag of interest rate level change to reflect the potential lag in the adjustment of the cost of capital of mortgage loans.

Prepayment would also depend on the current prime-HIBOR spread or the profitability ratio of the local banks. As the prime-HIBOR spread relates to the profit margin to the banks, the steepness of the prime-HIBOR spread would control the level of competition of the banks in giving loans.

When the prime-HIBOR spread is high, many banks will offer loans and mortgagors will refinance their existing mortgages with these mortgage loans with more attractive terms. This greatly stimulates the refinancing activities.

When the prime-HIBOR spread is low, smaller banks may not want to provide loans and therefore the prepayment process will be slowed down. On the part of mortgagors, this would also indicate the willingness of theirs to disinvest as captured similarly in v_3. This implies a faster prepayment for the period when the prime-HIBOR spread is higher. We thus expect $\beta_4 > 0$. We use the difference between the prime rate and the one-month HIBOR rate for this covariate,

$$v_4(t) = Prime\ Rate^{t-1} - HIBOR\ one\ month^{t-1} \qquad\qquad (8)$$

While it can be rigid to change, the prime rate could be roughly thought of as the long-term interest rate. And the Hong Kong interbank offered rate (HIBOR) could be considered as the short-term interest rate.

We also consider the effect of the rise in house prices on the prepayment rate. For speculators, a slight fall in house prices would signal a possible downturn of the housing market. This may trigger prepayments because the underlying property is more likely to be sold to reap the capital gain. We will thus expect the prepayment to speed up when the house price decreases. If we set

$$v_5(t) = 100 \times log\left(\frac{Propety\ index\ of\ this\ quarter}{Property\ index\ of\ the\ previous\ quarter}\right) \qquad (9)$$

We therefore expect that $\beta_5 < 0$. We use quarterly data for property prices here because we are not able to find data at monthly frequencies.

The prepayment behavior of a homeowner with a higher cost of capital could be very different from that of an ordinary homeowner. Some mortgagors would have easy access to additional funds and some would have difficulties to access the capital. These two different types of mortgagors would display totally different behaviors in terms of selling their property and thus their prepayment behavior would also be different. We control for this effect by using the loan-to-value (LTV) ratio at the loan closing time. Presumably people borrowing with smaller LTV ratios tend to have easier access to capital, and so they will tend to prepay as soon as the economic situation becomes unfavorable. In the empirical study, instead of the LTV ratio, we use variable that we call the relative LTV ratio. The relative LTV ratio is generated by using the LTV ratio divided by a certain critical LTV ratio. This critical LTV ratio varies from time to time and is set by the corporation to safeguard against any unsafe lending.[3] For example, it was .90 in 1991 and .70 in 1994.

$$v_6(t) = Relative\ LTV = \frac{LTV\ of\ th\ loan}{The\ critical\ LTV} \qquad (10)$$

If the above economic reasoning prevails, we should expect $\beta_6 < 0$.

On the other hand, speculators or noise traders are more concerned with the short-term capital gains rising from their housing portfolio. As they think they have superior information, they tend to utilize as much leverage as possible.

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[3] The Hong Kong Monetary Authority also regulates the LTV ratio.

So a high LTV ratio may simply be indicative of speculative borrowings. These borrowers tend to resell the property and thus incur fast prepayments. If this economic reasoning dominates, we should expect $\beta_6 > 0$. Finally, seasonality may influence prepayment activity. We represent this covariate by the dummy variable, $v_7(t)$, defined by

$$v_7(t) = \begin{cases} 1 \text{ if } t = May \text{ - } August \\ 0 \text{ if } t = September \text{ - } April \end{cases} \tag{11}$$

More residential real estate transactions occur in the summer season if there is any relocation consideration. Hence, we should see $\beta_7 > 0$.

3. Estimation and Empirical Result

3.1 Data Description and Maximum-Likelihood Estimation

Given the assumed prepayment function and available mortgage data from corporation P,[4] we will estimate statistically the significance of seasoning as well as the posited covariates in influencing a mortgagor's prepayment decision. We employ the method of maximum likelihood. That is , we determine the prepayment function's parameter values that are most plausible in light of the observed prepayment activity.

The data provided to us by Corporation P consists of 8865 loans, with a total value of around 12 billion Hong Kong Dollars. The data includes the origination date, the prepayment date, original property price, location of the property, characteristics of the mortgage and the monthly payment history. While more than half of the loans originated after 1994, some of the loans started as early as 1981. So we have roughly a cross section of 16 years of mortgage loan data. All the loans we have are adjustable rate mortgages and should be still repaying if not prepaid.

Of these 8865 loans, 262 of them have been partially prepaid. The 262 partially prepaid loans are important in that a proper usage of this information could help us to pin down the contribution of the partial prepayment to the prepayment behavior. The rest of the mortgages consist of 3089 prepaid loans and 5414 continuing loans. The age of the prepaid loans, when prepaid, has a mean of 2.6 years and a standard deviation of 2.1 years. Since there is no prepayment before March 1994, it seems that the data has been self-censored. We miss the prepayment information prior to March 1994. Because of the

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[4] Due to a confidentiality agreement, we cannot reveal the name of the corporation.

censorship problem, we will conduct the estimation on both the full dataset and the dataset with all loans originated before March 1994 truncated, or the truncated dataset. For the truncated dataset, we have 1260 loans prepaid up to 1997 and 4124 continuing loans, for a total of 5384 loans. See Figure 1a-b for a picture on when the loans were initiated and when they were prepaid.

The data are organized into four samples: the full sample with partial prepaid loans, the post-1994 sample with partial prepaid loans, the full sample without partial prepaid loans, and the post-1994 sample without partial prepaid loans. The four samples, as suggested by their names, could reveal the prepayment information from various perspectives. While the full dataset may provide us with more information, the partial dataset gives us more accuracy. Thus, when we interpret the estimation, we shall bear in mind that the truncated dataset is limited in the sense that the maximum age of the loan is only three years for the post-94 samples and that there is a censorship issue involved for the full samples.

Table 1 and Table 2 presents the summary statistics of all the variables used in our empirical studies for both the prepaid loans and the continuing loans respectively. While $v_1, v_2. v_3$ summarize the general economic conditions, the other factors are individual loan characteristics. As can be seen from the tables, the prepaid loans are older than the continuing loans on average. The following casual comments can be made based on the statistics of the table: the prepayment tends to happen at a time 1) when the rate markup changes more adversely, or 2) when prime increases, or 3) when term structure is steeper, or 4) when the property price rises mildly. All these remarks would be confirmed by our maximum likelihood estimation of the next subsection.

To have a better idea of the general economic condition of the period we studying, Figure 2a-b presents in picture the interest rate changes and property price change during the sample period**.** The difference between the line "Prime+Markup" and the line "Prime" in Figure 2a will give us some ideas about v_1. As can be seen, the markup has been decreasing through the time. The movements of v_3 and v_4, as they can be derived from the time series prime rate and the HIBOR rate, are also shown in Figure 2a. The movement of the housing price index, v_5, is shown in Figure 2b.

Figure 1a: Number of Loans Originated in Each Month
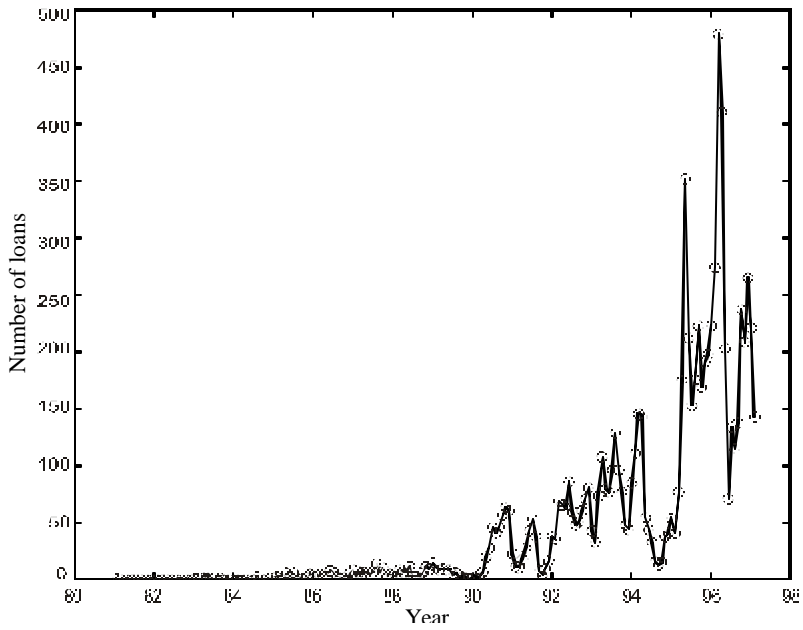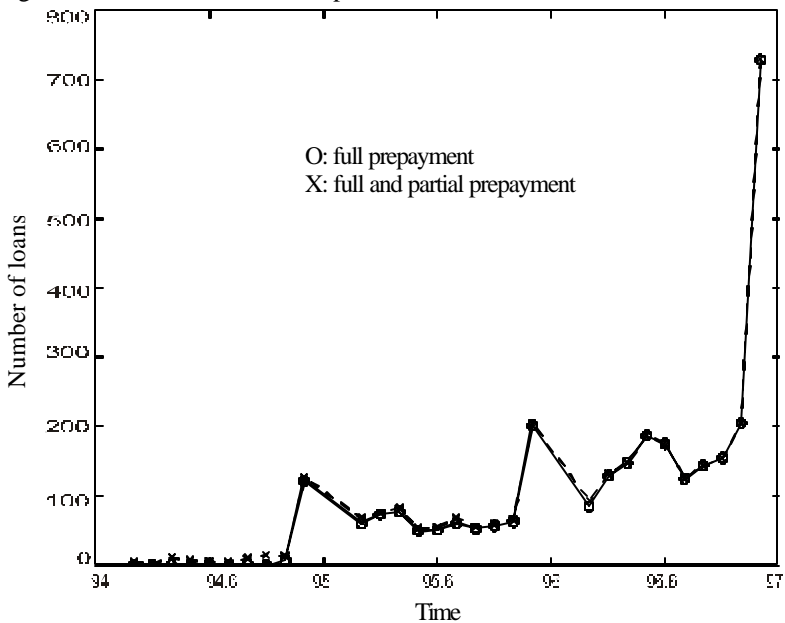
Figure 1b: Number of Loans Prepaid in Each Month

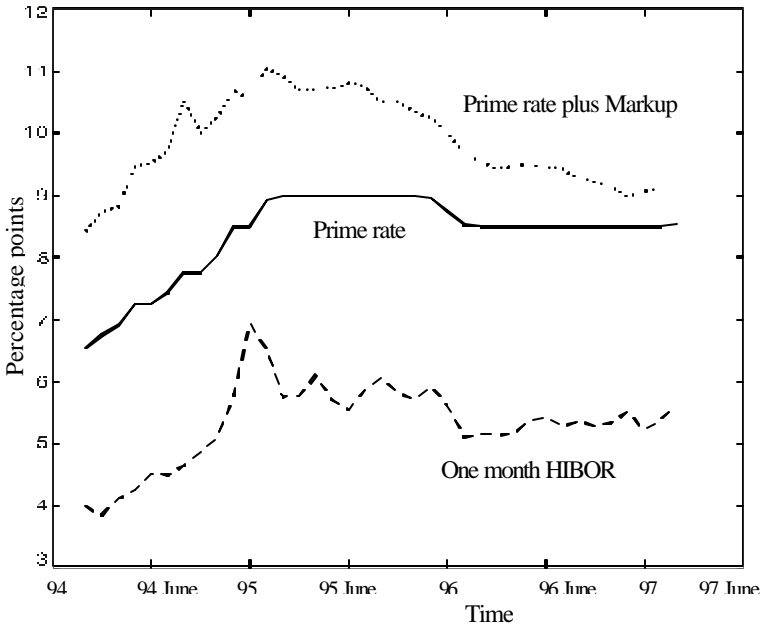Figure 2a: Movement of Interest Rates
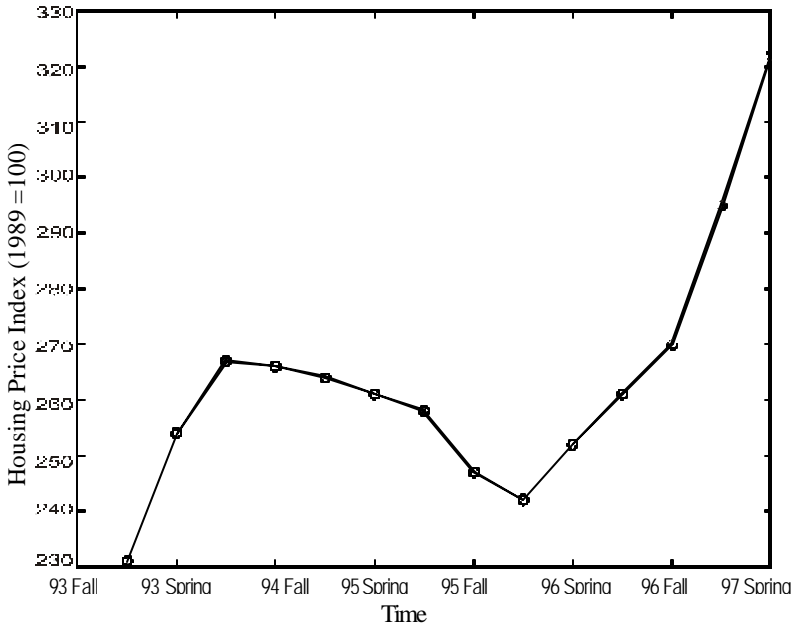
Figure 2b: The Trend of Housing Prices

Table 1: Summary Statistics of Factors Used: the Prepaid Loans

Variable	Description	Mean	Standard Deviation
Age	Age of the loan (year)	2.666	2.186
v1	The markup change	- 0.708	2.459
v2	The cubic of the markup change	-347.286	11889.3
v3	Change of prime rate	0.021	0.103
v4	Slope of term structure	3.112	0.167
v5	Property price change	3.449	4.502
v6	Relative Loan-to-Value ratio	0.654	0.391
v7	Summer dummy	0.302	0.459

Note: The summary statistics are generated based on the full sample with partial prepayment and is generated using the prepaid / partially prepaid loans only. The variables take the value at the time of prepayment or partial prepayment.

Table 2: Summary Statistics of Variables Used: the Continuing Loans

Variable	Description	Mean	Standard Deviation
Age	Age of the loan (year)	1.920	2.021
v_1	The markup change	- 0.045	0.954
v_2	The cubic of the markup change	-15.793	863.858
v_3	Change of prime rate	0	0
v_4	Slope of term structure	2.768	0
v_5	Property price change	8.758	0
v_6	Relative Loan-to-Value ratio	0.614	0.415
v_7	Summer dummy	0	0

Note: The summary statistics are generated based on the full sample with partial prepayment and is generated using the continuing loans only. The variables take the value at the endpoint of the sample. The O standard deviations appear because the variables representing economic condition takes a single value.

Denote the set of prepaid mortgages with I=1,2,…,I, and the set of surviving mortgages with j=1,2,…,J. Then assuming the conditional independence of prepayment decisions across time and across mortgages (given the posited $\underline{v}(t_k)$, where t_k denotes the age of prepayment or the age of the surviving loans.), the resultant logarithmic likelihood function is given by

$$\ln L(\boldsymbol{q}) = \sum_{i=1}^{I} [\ln \boldsymbol{g} + \ln \boldsymbol{r} + (p-1) \ln(\boldsymbol{g}_i) - \ln(1 + (\boldsymbol{g}_i)^p) + \sum_{h=1}^{s} \boldsymbol{b}_h \boldsymbol{n}_h(t_i)$$

$$- \exp(\sum_{h=1}^{s} \boldsymbol{b}_h \boldsymbol{n}_h(t_i)) \ln(1 + (\boldsymbol{g} t_i)^p)] - \sum_{j=1}^{J} \exp(\sum_{h=1}^{s} \boldsymbol{b}_h \boldsymbol{n}_h(t_i)) \ln(1 + (\boldsymbol{g}_i)^p) \qquad (11)$$

The above likelihood function diverges with $\gamma \to 0$ and $p < 1$. The model is thus not unidentifiable unless we are willing to restrict γ. We did exactly this in our empirical study and a lower bound is set for γ. We could also use some other hazard functions of other parametric families in our study. The reason why we chose to use this particular model is that this model captures the effects of seasoning in a very nice way.

3.2   *Empirical Result and Discussion*

We have done our numerical exercises with all four different data samples. The maximum likelihood estimation generates a series of estimates for the parameters in our proportional hazard model as we illustrated in Table 3. Bootstrapping is conducted to generate the standard deviations for the estimates. They give us some idea of the significance of the estimates. We have similar estimates for all the different data samples. The estimated coefficients for all factors have the same sign across different samples.

Table 3: The Estimates of the Model with Different Samples

	F. S. w. P		F. S. w/o P.		P-94 S. w. P		P-94 S. w/o P.	
	Est.	std. dev.	Est.	std. dev.	Est.	std. dev.	Est.	std. dev.
γ	0.136	0.007	0.136	0.004	0.136	0.010	0.135	0.007
p	1.307	0.032	1.209	0.009	1.402	0.038	1.416	0.058
β_1	-0.012	0.002	-0.021	0.001	-0.014	0.001	-0.018	0.001
$\beta_2(10^{-6})$	2.503	0.122	3.150	0.093	3.060	0.085	3.612	0.115
β_3	0.112	0.084	0.978	0.100	0.133	0.007	0.535	0.090
β_4	0.440	0.023	0.396	0.014	1.095	0.045	1.027	0.046
β_5	-0.104	0.004	0.093	0.004	-0.241	0.008	-0.221	0.008
β_6	-0.213	0.026	-0.274	0.015	-0.142	0.025	0.057	0.034
β_7	0.045	0.023	0.315	0.012	0.028	0.038	0.302	0.098

Note: This table gives the maximum likelihood estimates and their standard deviations with four samples. In the table, F.S.w.P. stands for "Full Sample with Partial-Prepaid loans", F.S. w/o P. stands for "Full Sample without Partial-prepaid loans", P-94 S.w.P. stands for "Post-94 Sample with Partial-Prepaid loans", P-94 S. w/o P. stands for "Post-94 Sample without Partial-Prepaid loans". Here Post-94 sample means the sample of data with all loans originated before 1994 truncated. The standard deviations are generated by bootstrapping.

Rate markup increases have a negative effect on the prepayment as expected. Namely, the lower the current markup, the more probable it is that a mortgagor tends to repay. The prime rate increase also has a negative effect on the

prepayment. This is consistent with the hypothesis that prepayment is a response to the payment shock of rising mortgage payments. These results are consistent with Lea and Zorn (1986). The coefficient of the cubic term β_2 is highly significant, which again demonstrates the importance of modeling the potential nonlinearity as suggested in Schwartz and Torus (1989).

Judging from the coefficient of v_4, the effect of a steeper prime-HIBOR spread would induce a higher prepayment speed. This result, if we take the variable as a proxy for the slope of the term structure, is inconsistent with Huang and Xia (1995). In their paper, they find a flatter term structure would increase prepayment speed. The underlying reason for our result, we think, may lie in the totally different structure of the Hong Kong mortgage loan market. Competition between the banks at the high Prime-HIBOR spread period may lead to a great deal of prepayments and thus a different sign of the coefficient.

The property price increase would have a negative effect on the prepayment speed as can be seen from the estimates of β_5. At times of rapid price increase, prepayment would be significantly slowing down. This result is sensible given the potential short-term continuation of property price as demonstrated in Case and Shiller (1990). A rise of property price tends to be followed by a further increase of property price and this would reduce the possibility of potential housing turnover. The result is consistent with the result in Lea and Zorn (1986).

The effect of the loan-to-value ratio on the prepayment speed β_6 is negative. This seems to suggest that the lower LTV ratio is indicative of an easy access to additional funds and the mortgagor would prepay as long as the economic condition becomes unfavorable. Also there seems to be a "summer effect" as suggested by most mortgage prepayment research.

In figure 3a-b, we plot the implied survival probability and hazard rate for these two sets of estimators with all the covariates fixed at the mean level. As we discussed in section 3, the post-94 sample gives us better information in the prepayment behavior for the first three years and the full dataset gives us better information in the prepayment behavior for those years after the third year. Some salient features of the pictures are: the hazard rate first goes up and peaks around the third year and goes down slowly for the following years. Partial prepayments only contribute a small portion to the total prepayments. According to the picture given by the full sample, we could keep around 40% of the mortgages in five years and 20% of the mortgages in ten years.
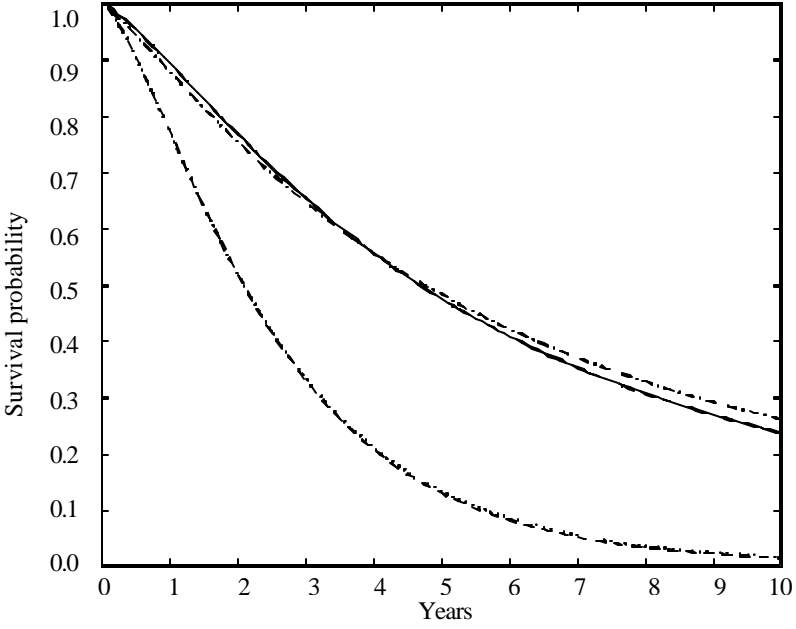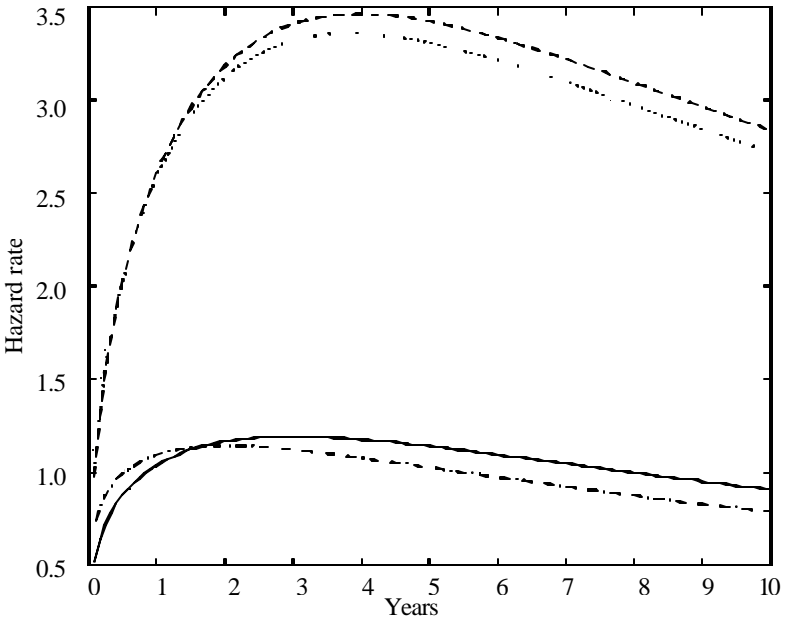
Figure 3a: Survival probability in 10 years

Figure 3b: Hazard rate in 10 years

Given the estimated prepayment function, the prepayment risk associated could be figured out by simulations. Since much research has been done on it, we will not go into that in the current study. Anybody who is interested in that kind of exercise, please refer to Huang and Xia (1996) or Kau, Keenan, Muller and Epperson (1990).

4.   Conclusion

As demonstrated by McConnell and Singh (1991), the value of ARM-backed securities with a proper modeling of prepayment could be significantly different from its value when the prepayment is absent. As the financial community of Hong Kong sets to securitize its huge assets of residential mortgages, a careful analysis of the prepayment behavior of the local mortgagors like ours is thus called for. Our study also contributes to the study of ARMs prepayment in general as there is rarely an environment with ARM of plain vanilla type as the dominant mode of mortgages. Our study is of value also in that the analysis in this paper has been made on the basis of micro-level data.

Our empirical result suggests the following, 1) Prepayment speeds up and then slows down as the mortgage seasons; 2) Prepayment speeds up as the rate markup decreases; 3) Prepayment speeds up as the interest rate increases; 4) Prepayment speeds up when the profitability ratio (the prime-HIBOR spread) is higher; 5) Prepayment speeds up as the price of the property market falls; 6) Loans with lower loan-to-value ratios tend to be prepaid faster; 7) Prepayment exhibits a seasonal pattern: people tend to prepay in the summer.

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