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Long range dependency and forecasting of housing price index and mortgage market rate: evidence of subprime crisis

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A B S T R A C T

In this paper, we examine and forecast the House Price Index (HPI) and mortgage market rate in terms of the description of the subprime crisis. We use a semi-parametric local polynomial Whittle estimator proposed by Shimotsu et al. (2005) [Shimotsu, K., & Phillips, P.C.B. (2005), Exact local Whittle estimation of fractional integration. *The Annals of Statistics*, 33(4), 1890-1933.] in a long memory parameter time series. Empirical investigation of HPI and mortgage market rate shows that these variables are more persistent when the d estimates are found on the Shimotsu method than on the one of Künsch (1987) [Künsch, H.R. (1987). Statistical aspects of self-similar processes. In Y. Prokhorov and V.V. Sazanov (eds.), Proceedings of the First World Congress of the Bernoulli Society, VNU Science Press, Utrecht, 67-74.]. The estimating forecast values are more realistic and they strongly reflect the present US economy actuality in the two series as indicated by the forecast evaluation topics.

1. Introduction

An immense paper has been under taken the subprime market crisis both in the US and worldwide (see Himmelberg et al. (2005), Case and Shiller (1987, 1989)), although many of the vectors by which transmission was spread through monetary markets are to be found in the considered product market or during the trading of credit derivatives among banks. The crisis has been caused by the non-payment of households on their house loans. This work focuses on the household's decision, asking the question: what stimulates a house to default on its credit? To address this question, we focus on the household's choice. Such a model deduces that a household chooses the non-payment or prepay their credit in such a way to maximize their prosperity[1]. In the United States, the general house prices increased from 93% to 137%, depending on the catalogue employed between 1996 and 2006. Some markets such as Los Angeles and Las Vegas, had smooth stronger house price expansion. At the identical time, mortgage

[1]Because the loan is a responsible to the household of minimise the price of the credit.

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interest rates were tremendously losing, and mortgage initiation of quantity increased quickly from \$800 billion in 1996 to a height of \$3.9 trillion in 2003.[2] Housing prices had been usually increasing during 2006, while the S&P500 series and the OFHEO[3] series demonstrated diverse exit points. Mortgage loan performance had begun to show signs of deterioration previous to the elevation of the housing price accumulator. One of the problems opposite to the monetary institutions that have also originated from subprime loans or have purchased subprime asset-backed securities is that, the reject in housing prices has contributed in the remarkable augmentation in subprime and mortgage defaults. Though there are other motivations for non-payment because borrowers who if not might have sold the possessions or refinanced when they hit a monetary difficulty, they no longer have these options. We investigate the best default decisions, which can be used to compute the probabilities of the default as an important contribution of risk management and pricing purposes. In this paper, we will examine and forecast the HPI index and mortgage market rate in terms of the description of the subprime loans that were initiated and their contribution in the decline in the housing prices[4]. The likely presence of a stochastic long memory in financial and economic time series has been an important subjects of together a theoretical and an empirical study. The long-memory (or long-term dependencies property) explain the high-order correlation organization of a series. If a series display a long memory, there is a persistent and a temporal dependence among observations widely separated in time. Such series display hyperbolically decaying autocorrelations and low-frequency spectral distributions. Fractionally integrated processes can provide rise to a long memory (Mandelbrot, 1977; Granger & Joyeux, 1980; Hosking, 1981). On the other hand, the short-memory, or the short-term dependence property explains the low-order correlation structure of a series. The short-memory series are typified by quickly declining autocorrelations and high-frequency spectral distributions. Standard autoregressive moving average procedure cannot display the long-term low frequency dependence as they are able to only illustrate the short-run high-frequency performance of a time series.

The paper is organized as follows: section 2 presents the literature review; section 3 presents the local Whittle process for forecasts and its main properties and section 4 contains applications real data of house price index and mortgage market rate.

2. Literature Review

A number of readers may accept question an analysis of the validity of when modelling the performance of households, many of whom may be considered to require monetary difficulty. On the other hand, the availability of micro altitude data for individual mortgages has facilitated to the econometricians to examine whether households affect their choice optimally or not. Stanton (1995) studied the choice by FRM borrowers to refinance their credits. While Deng et al. (2000) and Calhoun and Deng (2002), studied the fixed and the adjustable mortgage rate, respectively FRMs and ARMs loans providing evidence that empirically, households non-payment and refinancing results seem to be strongly influenced by the moneyless of the relation options. As noted in Deng et al. (2000), while the real options difficulty which is faced by households is a complicated one, the situation under which they should exercise their choices can often be quite easy to decide if the household can examine the market

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[2] See Pafenberg (2005) for a detailed examination of data from the Home Mortgage Disclosure Act composed with the Federal Financial Institutions Examination Council, data together and available by Inside Mortgage Finance and the Monthly Interest Rate Survey from the Federal Housing Finance Board. The data named here are from HUD's Survey of Mortgage Lending Activity, Inside Mortgage Finance, and Freddie Mac.

[3] The two mainly often named indices are the S&P500 Index and the Office of Federal Housing Enterprise Oversight (OFHEO) House Price Index.

[4] Ambrose and Sanders (2004), Pence (2006), Cutts and Merrill (2008) and others have tested the importance of situation system in this learn of mortgage markets.

prices for their mortgage.[5] Briefly, we will not present an extensive literature review here, preferring to hear on a few key works. With respect to the measurement of house price tendency, there has been a substantial effort expended over the years in the creation and evaluation of option house price index. More importantly, such index is based on median sales prices estimates. Case and Shiller (1987, 1989) who primary tell the repeat-sales estimation technique, which is now usually regarded as the most excellent available method for assessing the house price movements in excess of time because it is the only technique that is intelligent statistically to approach closer to eliminating the possible biases associated with the uncontrolled variations in neighborhood or structural facilities across units.

Himmelberg et al. (2005) studied well the aptitude of economic fundamentals to describe recent house price patterns, constructing measures of the yearly cost of single family housing for 46 city areas in the United States during the period 1995-2004 and compared to the costs of renting. They dispute that metrics such as the expansion-rate of house prices, the price-to-rent relation, and the price-to-income ratio do not pass to account together for the time series outline of real long-term interest rates and predictable differences in the long-run augmentation rates of house prices across domestic markets. They found that at the beginning of 1995-2004, the cost of owning had increased more than the cost of renting, but not, in most cities, to levels implying that houses had been overvalued. Another thread of literature focuses on supply constraints. Glaeser et al. (2005) heart on narrow constraints touching the elasticity of housing provides. They dispute that a deteriorating supply elasticity resulting from increased local development regulations in certain cities has caused prices to rise excessively in recent years. These arguments are steady with Malpezzi (1999a, 1999b) and Malpezzi and Maclennan (2001) that cross-sectional disparity in regulatory constraints assists explain volatility in house price dynamics during its effect on supply elasticity. In this study, we believe that the k-factor Gegenbauer process, which is a k-factor GARMA process lacking the autoregressive and moving-average parts. We put our attention on forecasting with this process and we offer the exact analytic expression of the prediction function and its MSE, which are new results. More precisely, our approach presents the following distinctive features: first, we believe that the case for which the parameters are known. We give the analytic expression of the h-step-ahead predictor derived as of the k-factor Gegenbauer model, and we give its confident limits and the MSE of prediction. Secondly, we consider the case for which the parameters are imprecise, and we estimate them by means of the quasi-maximum likelihood method of Whittle. We provide then the h-step-ahead forecaster from the k-factor Gegenbauer model; the confidence limits and the MSE are only given for $k = 1$. The cause is that, up to now, the limiting distribution of the Whittle estimator of parameters is only identified for $k = 1$, see Ferrara and Guegan (1999). Note that if the position of the unbounbed peaks of the spectral density is identified, then the limiting distribution of the Whittle's estimator of the long memory parameter d will be given by Hosoya (1997). Finally, we provide two applications to real data housing price index and real mortgage rate and we compare the obtained results with other short and long memory approaches.

3. Econometric Methodologies

Such fractional integrated procedure has been studied by Beran and Terrin (1996), Velasco and Robinson (2000), Shimotsu and Phillips (2002, 2005), Abadir et al. (2007) and Moulines et al. (2008). In this work, we applied the local Whittle method and exact local Whittle technique process for estimating the parameter.

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[5] A similarity can be made to regular financial alternative exercise. If one can observe the market price of a call or put option, exercise is optimal when the exercise price equals the option's price.

3.1. Local Whittle advance

The other class of semi-parametric frequency domain estimators we believe follow the local Whittle approach suggested by Künsch (1987), which was analyzed by Robinson (1995), who called it a Gaussian semi-parametric estimator, and is attractive since its likelihood interpretation, nice asymptotic possessions and very class assumptions. The LW estimator is distinct to maximize of the (local Whittle likelihood) purpose:

$$Q(g,d) = -\frac{1}{m}\sum_{j=1}^{m}\left[\log\left(g\lambda^{-2d}{}_{j}\right) + \frac{I(\lambda_j)}{g\lambda^{-2d}{}_{j}}\right] \tag{1}$$

where $m = m(T)$ is a bandwidth number which tends to infinity as $T \to \infty$ except at a slower speed than T.

$I(\lambda) = \frac{1}{2\pi T}\left|\sum_{t=1}^{T} y_t e^{it\lambda}\right|^2$, is the periodogram of y_t, $g_x(\lambda)$ is the spectral density of y_t, $\lambda_j = \frac{2\pi j}{n}$, and $j = 1,\ldots,n$.

One disadvantage compared to log-periodogram estimation is that a statistical optimization is needed. On the other hand, the assumptions underlying this estimator are weaker than persons of the log-periodogram regression (LPR) estimator. Robinson (1995) showed that while $d \in \left(-\frac{1}{2},\frac{1}{2}\right)$;

$$\sqrt{m}\left(\hat{d}_{LW} - d\right) \xrightarrow{d} N(0,1/4) \tag{2}$$

Therefore, the asymptotic distribution is extremely simple, facilitating easy asymptotic inference, and in particular the estimator is more efficient than the LPR estimator. The ranges of reliability and asymptotic normality for the LW estimator have been shown by Velasco (1999) and by Phillips and Shimotsu (2005) to be the same as those of the LPR estimator. An exact local Whittle (ELW) estimator has been planned by Shimotsu and Phillips (2005) that avoids some of the approximations in the divergence of the LW estimator and is valid for any value of *d*. The ELW estimator replaces the object function (1) by the purpose:

$$Q_E(g,d) = -\frac{1}{m}\sum_{j=1}^{m}\left[\log\left(g\lambda^{-2d}{}_{j}\right) + \frac{I_{\Delta^d X}(\lambda_j)}{g}\right] \tag{3}$$

where $I_{\Delta^d X}(\lambda) = \frac{1}{2\pi T}\left|\sum_{t=1}^{T}\left(\Delta^d y_t\right)e^{it\lambda}\right|^2$ is the periodogram of $\Delta^d y_t$. The ELW estimator assure (3) for any value of *d* and is thus not restricted to any exacting range of d values, but it is limited to zero-mean processes. In addition, Shimotsu (2002) projected the feasible ELW (FELW) estimator. Andrews and Sun (2004) proposed a generalization of the local Whittle estimator, the local polynomial Whittle (LPW) estimator of d designed for $d \in \left(-\frac{1}{2},\frac{1}{2}\right)$.

For both the log-periodogram regression technique and the local Whittle approach, the alternatives of bandwidth parameter *m* are very significant. Results on optimal (minimizing the sum mean squared error) choice of bandwidth for the log-periodogram regression have been interpreted derived by Hurvich et al. (1998), and results of the local Whittle approach have been derived by Henry and Robinson (1996). In both cases, the optimal bandwidth is said to be multiplied by $T^{0.8}$, where the multiplicative stable depends on the smoothness of the spectral density near the source, i.e., on the short-run dynamics of the procedure.

3.2 Diverse classifications of $I(d)$ processes

Two main advances to indicate an $I(d)$ process have been used in the literature until now. They are by no means total. The first, which is old in Hosking (1981) among others, is to suppose $d < \frac{1}{2}$ and define the observed process y_t as an infinite order moving average of short-dependency novelty

$$y_t = y_0 + (1-L)^{-d} u_t = \sum_{k=0}^{\infty} \frac{(d)_k}{k!} u_{t-k} \tag{4}$$

where u_t is a feebly dependent stationary process, y_t is stationary when $d < \frac{1}{2}$. This advance is extended by partial summation structures to produce $I(d)$ series with $d \in \left[\frac{1}{2}, \frac{3}{2}\right)$. Exacting, the observed $I(d)$ process y_t is distinct as the partial sum of a stationary fractionally integrated process of order $d-1$ (Hurvich & Ray, 1995; Velasco, 1999a, b),

$$y_t = y_0 + \sum_{j=1}^{t} z_j \quad , \quad t \geq 1 \tag{5}$$

where z_j is a stationary $I(d-1)$ process and satisfies

$$z_t = (1-L)^{1-d} u_t = \sum_{k=0}^{\infty} \frac{(d-1)_k}{k!} u_{t-k} \tag{6}$$

3.3. Forecast of HPI and mortgage rate index

There exists much literature about the forecast for stationary processes (see for instance, Geweke and Porter Hudak (1983), Noakes et al. (1988), Ray (1993), Smith and Yadav (1994), Crato and Ray (1999), Barkoulas and Baum (1997) and Brodsky and Hurvich (1999)). As for the forecast of the non-stationary process, to our information, there exists almost no literature for reference. In this work, since we proposed a new non stationary process jointly with a reliable and robust wavelet-based estimation technique, it is necessary to give out a procedure of the forecast for this novel model. It is known that the best prediction on a horizon h for a time series y_t is in the sense of the minimum mean square error (MSE). The forecast provided by the predictor of least squares method is given by the predictor of least squares method which is given by the following expression:

$$\hat{y}_t(h) = E(y_{t+h} | I_t), \text{ where } I_t = \sigma(y_s, s \leq t) \tag{7}$$

We measure the forecasting aptitude of the model by considering the root mean square error (RMSE) of prediction. The criteria are defined as follows:

$$RMSE = \sqrt{\frac{1}{h} \sum_{l=1}^{h} \left(y_{t+l} - \hat{y}_t(l)\right)^2} \tag{8}$$

where h is the forecast horizon and $\hat{y}_t(l)$ is the predicted value of y_{t+l}, see Priestley (1981) for reference. Now, we consider the forecast for non-stationary processes, particularly the locally stationary *k*-factor Gegenbauer process that we have indicated by:

$$\prod_{i=1}^{k} \left(I - 2\cos\lambda_i B + B^2\right)^{d_i(t)} y_t = \varepsilon(t) \tag{9}$$

where $(\varepsilon_t)_t$ is white noise with variance σ_ε^2

Our strategy for the prediction of the locally stationary *k*-factor Gegenbauer process is as follows:

1- Make the *n*-step-ahead predict for the long memory structure functions $\hat{d}_t(h) = E\left(d(t+h) \middle| I_t\right)$.

We begin by the estimations of $\hat{d}_i(t)$ obtained by the wavelet-based algorithm which is smoothed by spline technique. It is the prediction for the estimated polynomial curves. Then, we can develop the previous operator in the next way:

$$\prod_{i=1}^{k}\left(I-2\cos\lambda_i B+B^2\right)^{d_i(t)} y_t=\sum_{n=0}^{\infty}\pi_n(t)B^n \tag{10}$$

and the coefficients $\pi_n(t)$ verify:

$$\pi_n(t)=\sum_{\substack{0\le j_1,\dots,j_k\le n\\ j_1+\dots+j_k=n}} c_{j_1}^{(-d_1(t))}(\cos\lambda_1)\dots c_{j_k}^{(-d_k(t))}(\cos\lambda_k) \tag{11}$$

in which $c_k^{(d(t))}(x)\,c(d(t))$ are orthogonal Gegenbauer polynomials we defined on $[-1,1]$. Thus, we get the following proposition which ensures the continuation and locally stationary conditions for the locally stationary *k*-factor Gegenbauer development.

2- Calculate y_t with the Eq. (10) and Eq. (11).

To specify, presume that we have the series $y_1,\dots,y_T$ which has been modelled by the locally stationary *k*-factor Gegenbauer process (9), and the estimating time-varying parameters are $\hat{d}_i(t), t=1,\dots,T$. First of all, we make the *n*-step-ahead prediction $\hat{d}_i(T+h)$ $(h=1,\dots,n)$ for the time-varying long memory parameters. One smoothing curve is obtained by the cubic smoothing spline method. We predict a smoothing spline which fits at novel points. The predicting fit is more linear than the original data. The other smoothing curve is obtained by the loess method using local fitting a polynomial outside resolute by one or more numerical predictors. According to the results of Monte Carlo experiments, when the degree of smoothing is 0.75, the estimating behaviour seems to be the best for the loess method with comparison to the other degrees of smoothing. A few iterations of an estimation procedure with house price and real mortgage rate index are used to realize the forecast of $\hat{d}(t)$. Then, we find the forecast $\hat{y}_{T+h}(h=1,\dots,n)$ using the orthogonal Gegenbauer coefficients. To validate the behaviour of this predict, we measure the corresponding bias and RMSE.

4. Data and Results

We used a monthly house price and mortgage market rate index from January 1991 to November 2008 and from January 1990 to September 2009 respectively. The HPI is estimated with data on repeat transactions found by combining data on single-family mortgage acquisitions given to OFHEO by the activity. About one month following the end of each sector activity data on all single-family mortgage depression for the previous quarter is delivered to OFHEO on computer group.

Table 1
Descriptive statistics of House Price Index (HPI) and the mortgage market rate

	HPI	Rate mortgage
T	215	237
Mean	191.35	7.235
Variance	8878.35	1.622
t-statistic	29.77*	87.44*
Skewness	0.63	0.501
Kurtosis	-1.21	-0.307
Jarque-Bera	27.54	10.857

Note: Jarque-Bera denotes normality test statistic. * denotes significance at 1% level.

Table 1 provides a summary statistics for all of the data elements in our analysis. The descriptive statistics compute to the moments, skewness, kurtosis and normality of the HPI and mortgage market rate series. The returns series of the highest standard deviation are valuating in the crisis period (from 2006 to 2007). The Jarque-Bera statistics in all periods facilitate to reject that series is normally distributed by referring to the p-values. The returns data exhibit the fat-tailed occurrence and the kurtosis is more than 3 for both series.

Table 2
Integrated test of HPI and mortgage market rate index

	HPI	Rate Mortgage
AIC	1.939	-3.156
BIC	1.971	-3.126
p,q	2,1	2,1
ADF 1	2.239	-3.706
ADF 2	4.012	-
ADF 3	2.602	-
PP	0.344	-1.789
KPSS	4.046**	3.702**
constant	298.48	6.387
$\hat{\alpha}_1$	1.92 (0.00)	0.933 (0.00)
$\hat{\alpha}_2$	-0.92 (0.00)	0.039 (0.81)
$\hat{\theta}_1$	-0.58 (0.00)	0.407 (0.00)
ARCH4	73065	2460

Note: NS and S indicate the no stationary and stationary respectively, **denotes significance at 1% level. ADF1 represent the ADF without constant, ADF 2 with constant and ADF 3 with constant and trend. The (.) denote the p-value.

Table 2 presents the no stationary of HPI process due to the large fluctuation of the subprime crisis and the stationarity of mortgage rate index because the existence of several changes. Table 2 presents results of the estimating ARMA (2, 1) models for the HPI and mortgage rate series. These results were also confirmed by the use of the autocorrelation and partial autocorrelation functions. Hence, the remarkably simple ARMA (2, 1) model was found to provide an excellent representation of the conditional means of the HPI and rate mortgage series. In general, the estimations of the $\hat{\alpha}$ parameter are fairly analogous to the corresponding estimations from a higher order ARMA (p, q) around a linear time trend. The HPI and mortgage rate series are relatively short series and it is desirable to use much longer series for the purpose of investigating possible HPI and mortgage rate change. Fig. 1 demonstrates remarkable augments in subprime lending strength over our observations period pre-testing shows our model is accurately characterized as an ARMA (2, 1) process. Seems at correlograms for price levels in our major reduced form model, we find a very strong serial correlation with a pattern characterized by first degree autocorrelation (Figs. 2). When we take monthly modify in home prices, autocorrelation is still fairly persistent. We use an iterative approach to address autocorrelation in housing price and rate mortgage index as well as probable simultaneous trends among prices and independent variables during our sample period. The HPI and mortgage rate estimations of the ARMA (2,1) error structure confirm the presence of autocorrelation in HPI and rate mortgage found in the pre-testing (Table 2). Table 3 presents the results of the Local Whittle and Local Polynomial Whittle of GARMA (p,d,q) estimators. As expected from theory, the LW and LPW estimators appear to float down biased and are decreasing in the bandwidth. For the LW estimator, the memory estimates that some of the HPI and mortgage rate index are in the stationary series, but for the most part, they are in the no stationary series. In Table 3, we present the results of the three variants of the LPW estimator. First of all, as expected from theory and the simulations above, it is clear that this estimator does not suffer from the descending bias that increases with bandwidth as is presented in the LW and Local Polynomial Whittle estimators. Secondly, we notice that the three diverse implementations of the estimator agree with every other for mainly stocks and bandwidth choices. Thirdly, the LPW estimates are comparable to the LW estimates, although the LPW estimates are slightly advanced on average. Tables 4 and 5 compare the average relative MSEs, RMSEs and MAEs of our models for the HPI and rate mortgage index. Since the results obtained for the ‘random sample’ cases are very similar in most respects, we have not reproduced them here for the sake of shortness but are prepared to supply them upon request. The winner in terms of average MSE reduction is the HPI model (which so far has rarely been considered as a model of volatility dynamics) behind HPI by at most one percentage point. Except for short horizons, the average forecasting quality of rate mortgage is quite inadequate. Interestingly, mortgage rate performs more inferior than other models even over relatively short term.

Table 3

Local Whittle estimation of long memory in HPI and mortgage market rate index

	HPI	Rate mortgage market
Local Whittle		
$\hat{d}$	1.053 (0.00)	1.066 (0.009)
GARMA (p,d,q)		
$\hat{\theta}_1$	1.016 (0.00)	0.958 (0.00)
$\hat{\theta}_1$	-0.149 (0.00)	0.166 (0.00)
$\hat{d}$	0.176 (0.00)	0.0101 (0.82)
Whittle-GARMA(p,d,q)		
$\hat{d}$	1.053	0.137

Note: the value between (.) denotes the p-value.

Table 4

Forecasting of HPI index out of sample

HPI	h=1	h=2	h=6	h=12	h=24
Mean absolute error	125.736	126.328	140.222	165.511	181.047
Root mean square error	125.736	126.329	140.603	166.503	181.738
Mean square error	15809.73	15959.04	19769.260	27723.27	33028.86
Tests U	30.148	30.29	24.51	33.26	41.65

Note: These univariate models were estimated from data until 2008 and then forecasts constructed for 1 through 5 periods ahead. The statistics the Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Squared Error (MSE) and Theil's U statistic were averaged over the ten forecast periods. The models were then re-estimated for data up to 1990 and the procedure repeated, and the last forecast origin of 2008.

Table 5

Forecasting of Mortgage Market Rate index out of sample

Rate Mortgage	h=1	h=2	h=6	h=12	h=24
Mean absolute error	1.64	2.128	2.197	2.062	1.653
Root mean square error	1.729	2.129	2.207	2.105	1.746
Mean square error	2.991	4.533	4.873	4.433	3.049
Tests U	22.475	22.568	8.445	6.747	6.81

The average development compared to naive predicted are in the range of up to about 0.46 (0.42) percent at one monthly horizons, 0.93 (0.84) percent at 2 monthly, 2.79 (2.53) at 6 monthly, 5.58 (5.06) at 12 monthly and 11.16 (10.12) percent at 24 monthly horizons respectively for HPI (mortgage market rate) index. To provide more details, tables 4 and 5 show box plots of the distribution of MSEs, RMSEs and MAEs over all 24 monthly, for all methods and time horizons. A glance at the range of results for the different methods reveals some interesting tendencies. It particularly shows that for all long-memory models the inter-quartile choice is under the benchmark of one for all time horizons. In contrast to mortgage rate, we find an improvement against the "naı¨ve" prediction in the majority of cases with these models so that mean values above 1 in tables 4 and 5 are due to extremely large entries in the higher end (the median is forever 1 for all methods). At the lower end, we find that for the one day horizon, MSE can be reduced against the naive forecast by more than 30 percent in one particularly successful application of the mortgage rate model. At the long horizon end (2 years forecasts), HPI and mortgage rate provide the best cases with 10 percent improvements over the naive prediction (with HPI series only having slightly worse 'best cases'). Fig. 1 depicts the fact that the house price and mortgage rate index in levels are monthly decreasing over the periods. Fig. 1 summarizes our loan density distributions over our observation period by instrument. Note the substantial augment in house price index in 2003, followed by a clear refuse beginning after January 2006. Oversized loans, by distinction, remain relatively constant in their image in the market, with even a small refuse after October 2004.

We examine afterwards whether this augment in subprime represents an augment in general lending or only a displacement of other loan types. This was only done in order to remove from the figures some short term volatility. Thus, making it simpler used to facilitate our observation of the long run dynamics. Though our results demonstrate no confirmation of subprime strength having an effect on the future housing returns, a potential endogenous among subprime intensity and housing returns must be noted. Our main problem has to do with subprime effect on home prices, but a separate question is: how does housing profits and mortgage rate effect subprime power? Given the elevated levels of autocorrelation in housing profits, it is probable that lenders relax (tighten) their lending principles when housing profits are positive (negative) since the borrower probably can (cannot) sell or refinance if credit payments develop into heavy. In this case, subprime intensity could emerge to have a result on future home prices when it is just the product of history housing returns. We find that the height of subprime intensity is indeed positively related to precedent housing returns (Table 3), although the degree of serial correlation in subprime strength inflates the statistical significance. This endogeneity provides experiential support to our assertion that subprime did not itself contribute to the run-up in housing prices in the mid 2000's, and reinforce our fight that subprime strength should not be measured a primary causal factor in housing returns. From Fig. 3, we remark on the stability HPI and mortgage rate index from early 2010, the end of the subprime crisis from 2010. With deference to our mortgage market and macro-economic variables, we establish that the aggregating level of mortgage lending, population growth and the HPI and mortgage rate index were the major variables heavy house prices. These activated primarily in the mid-level and high-level markets. Astonishingly, the level of mortgage significance rates was not established to have a significant relationship with home prices. The negative coefficient on aggregated house mortgage debt exceptional, especially at the high end of the market, is interesting and unexpected, although it is reliable with the results of LW above, in which augmented credit accessibility represents an ‘‘oversupply” of credit, driving down prices. We have found that the semi-parametric purpose has the advantage of being robust to any form of instability in the short memory component. When the order of integration itself changes, the highest one is estimated; the lower order of integration may at most induce a lower order bias, which can be avoided by removing the highest frequencies. Finally, we observe that the provided constraint index (HPI and mortgage rate series) is correctly positively signed and significant. This significance is however entirely at the high end of the market. Restrictive land used regulatory strategy does not emerge to drive low or middle level house prices upward, a result that has relevance of restrictive housing supply policies[6].

5. Conclusions

We also establish that previous to 2005, housing price changes in this situation were related to changes in gravely illegal mortgage rates, but their relationship was weak at best. Though, in the 2005-2008 periods, we establish that the relationship had fundamentally changed and that house price changes and seriously aberrant subprime mortgage rates were strongly related. That is, as housing prices sustained to fall, grave illegal subprime mortgage rates continued to increase. The results in this paper are important for risk managers at financial institutions, investors and government agencies in that it demonstrates that complicated risk management models which were based on past data can be deceptive if the relationship between housing prices and subprime non-payments were not correctly modelled. The unexpected concept change in 2005 and 2006 demonstrates that markets can change

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[6] It should be renowned that the Wharton Land Use Regulatory Index varied by MSA only and was measured constant over time and across house price tiers. This could have disguised possible property temporally and across individual MSA submarkets.

dramatically and the most complicated models can be taken by shock. In an empirical investigation of the HPI and mortgage rate index, the local polynomial Whittle with noise estimator, indicated a stronger determination in volatility than standard estimators, and for most of the stocks, produced estimates of d in the no-stationary process.

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Appendix

A1

Fig. 1. House price and Rate Mortgage Market index

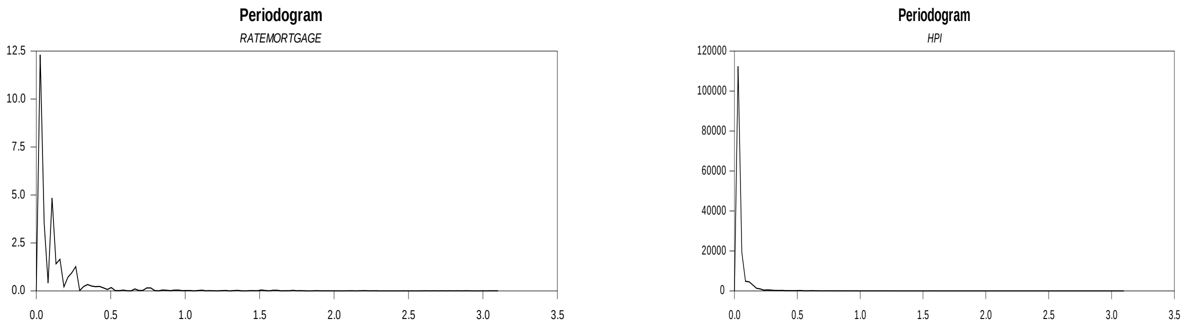

Fig. 2. The Periodogram of House price and rate mortgage index

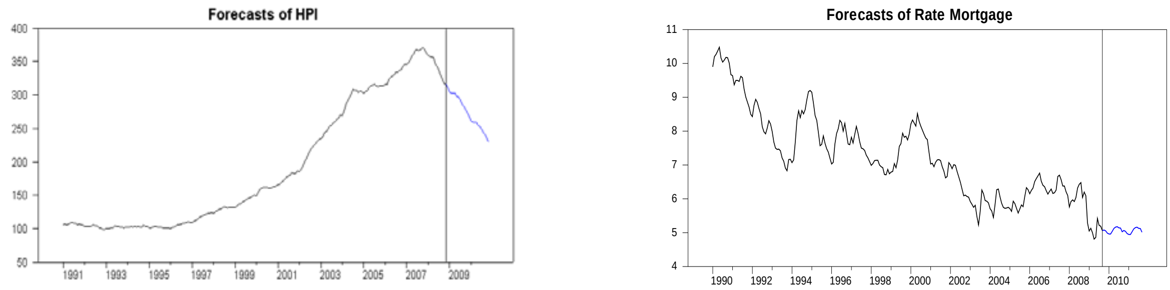

Fig. 3. The forecasting of House price and rate mortgage index

A.2

The predictable evaluation statistics presented in my coverage of economic forecasting are: the mean error *(ME)*, the mean squared error *(MSE)*, the mean absolute error *(MAE)*, the root mean square error *(RMSE)* and Theil's U-statistics. Theil's U-statistic is indicated in two of its specifications, these being labelled U_1 and U_2 respectively. Indicating a series of interest as y_t and a predict of it as f_t, the resulting forecast error is given as $e_t = y_t - f_t$, for $t = 1,...,T$. Using this notation, the (fairly standard) set of forecast evaluation statistics presented can be indicated as below:

$$ME = \frac{1}{T}\sum_{t=1}^{T} e_t\,,\quad MSE = \frac{1}{T}\sum_{t=1}^{T} e^2{}_t \text{ and } MAE = \frac{1}{T}\sum_{t=1}^{T} |e_t|\,, \qquad \text{(A.1.)}$$

- The U_1 statistic is bounded among 0 and 1, with values closer to 0 presenting greater forecasting accuracy. On the basis of the above arguments, rate mortgage index represents the 'best' set of predict of the four to amount. This is illustrated by the calculated U_1 statistic for rate mortgage index being the buck reported.

$$U_1 = \frac{\sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(y_t - f_t\right)^2}}{\sqrt{\frac{1}{T}\sum_{t=1}^{T} y_t^{\,2}} + \sqrt{\frac{1}{T}\sum_{t=1}^{T} f_t^{\,2}}} \qquad \text{(A.2)}$$

- The U_2 statistic will take the value 1 under the naive forecasting method. Values less than 1 indicate greater forecasting accuracy than the nave forecasting structure; values better than 1 indicate the opposite. When considering the statistics for HPI index it can be seen that while they return numerous values for the ME, MSE, MAE and RMSE, two forecasts return a value of 1 for the U_2 statistic as both are naive predict.

$$U_2 = \frac{\sqrt{\frac{1}{T}\sum_{t=1}^{T-1}\left(\frac{f_{t+1} - y_{t+1}}{y_t}\right)^2}}{\sqrt{\frac{1}{T}\sum_{t=1}^{T-1}\left(\frac{y_{t+1} - y_t}{y_t}\right)^2}} \qquad \text{(A.3)}$$