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Durations

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AFT Announces Loan Level Prepayment Model

Considers FICO, Geography, LTV, Loan Amount and Loan Purpose in generating prepayment vectors.

AFT is developing a new prepayment model that delivers a better understanding of prepayment propensity at the loan level by accepting key prepayment drivers. Current AFT clients can receive this upgrade without charge by requesting it from AFT client services. Future deliveries of the AFT Prepayment Model will be able to accept FICO, Geography, LTV, Loan Amount and Loan Purpose as indicatives.

Figure 1 - Historical Prepayment of a Pool of Mortgages (SMM)

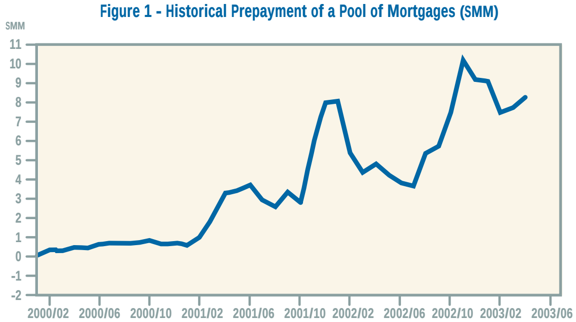


Figure 2 - AFT Model Performance vs. Historical Actual

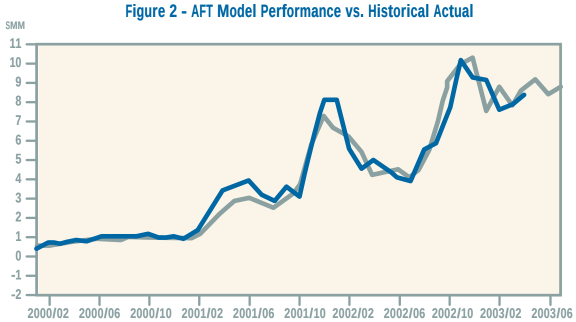
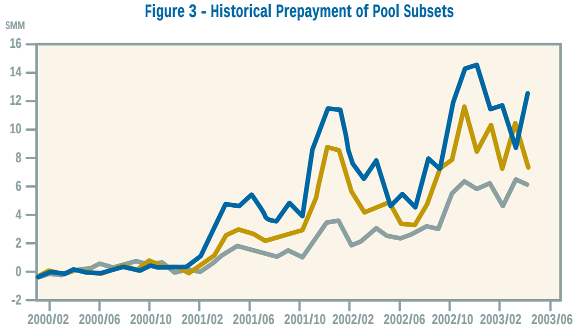


Figure 3 - Historical Prepayment of Pool Subsets



Why understanding loan level prepayments is critical

Mortgage market participants measure and understand prepayment risk at the pool level. The indicatives in the dominant prepayment models are weighted average coupon, weighted average maturity and loan type and original term. Billions of dollars of mortgages trade daily based upon models that forecast prepayments as a function of this limited set of information.

Loans and securities that are priced and traded homogeneously actually behave quite differently and should be valued differently. By understanding loan level prepayment, one can price, fund and hedge mortgages more precisely, improve returns and create sustainable competitive advantage.

The current understanding of mortgage prepayments

Figure 1 depicts historical single monthly mortality (SMM) of a pool of mortgages originated in 1999. SMM is a measure of the reduction in principal experienced by a mortgage pool in any given month. All of these loans have nearly the same coupon of 7.5% and were priced with the same prepayment expectations in August of 1999.

Figure 2 charts the prepayment forecast that AFT's model provided for this pool compared to the actual prepayment; given knowledge of future interest rates.

Figure 2 shows that AFT model performance versus historical actual model performance is excellent. Model users have a forecast of prepayment performance for the pool of loans in any future rate environment.

The loan level understanding of mortgage prepayments

Not all loans in the pool prepaid exactly as the pool prepaid. Individual loans and smaller groups of loans may prepay more quickly or slowly than the average. Therefore, they will have more or less value than the average, and require different pricing, funding and hedging strategies than the average.

Figure 3 depicts the historical prepayment of three different subsets of the original pool.

We can see that a subset of a pool of loans always prepays differently than other subsets of the pool. The opportunity for better than average performance lies in discovering these sub-pools and understanding how they will perform. The new AFT Loan Level prepayment model will allow AFT clients to understand how geography, LTV, loan amount, FICO and loan purpose drive prepayment behavior. For more information on this product contact us at *www.aftgo.com/loanlevel*.

Assessing the Forecasting Accuracy of Competing Prepayment Models: A Case Study

By David Sykes, Ph.D, David Sykes Partners, LLC

Introduction

How does a mortgage investor decide which prepayment model to use? Mortgage prepayment models are available from a number of third-party vendors and/or a portfolio manager may be confronted with multiple in-house alternatives. The choice of prepayment model is clearly a critical decision given that prepayment forecasts underlie the calculations of both the value and risk (e.g. duration and convexity) of a mortgage portfolio.

Unfortunately, however, determining the "best" model is generally not a straightforward process. "Best" has numerous dimensions. To sort some of them out, consider two extreme modeling perspectives:

1) Empirical: this perspective reflects the observation that history often repeats itself; thus a model is designed so that for given economic conditions (rate scenario etc), the prepayment forecast replicates as closely as possible the prepayments actually experienced when those same conditions occurred in the past.

2) Behavioral/theoretical: here the priority and emphasis is on accurate, detailed modeling of the decision-making process; a model's accuracy in replicating historical scenarios is a secondary consideration; behaviorists argue that fundamentals change and that the only hope of capturing the prepayment implications of these kinds of changes is detailed attention to modeling the essence of the decision-making process.

In practice, the "best" model will strike a happy balance between the two extreme positions. No one can be sure that the past will repeat itself and, of course, until it happens, one cannot know with certainty how well a given behavioral model will anticipate scenarios never before experienced. Thus, the modeler must judge as to the proper balance between the empirical and the theoretical, and the end-user (investor) is left to judge the modeler's acumen with regard to modeling issues as well the integrity of the modeler's claims.

Table 1. Mortgage Product Used In Study

Pools Analyzed :	22 pools of Fannie 30-Year Fixed Rate Mortgages
Min Pools Size :	$100 million
Vintages:	Nov 1992 to Aug 2001
WAC:	6.50 to 8.00%
Data Source:	Fannie Mae and Applied Financial Technology

Table 2: Statistical Tests of Forecast Accuracy

1) Average Absolute Error: the absolute value of the models' month-to-month forecast errors averaged over the forecasted time frame—measured in CPR.

2) Average Error: since positive and negative errors off-set one another in the calculation of an average, this statistic provides an overall indicator of a model's tendency towards over- versus under-prediction—measured in CPR.

3) Diebold-Mariano Statistic: this technique assesses the relative size of the models' month-by-month forecasting errors; the square of BRAND X's monthly errors are subtracted from the corresponding squared errors of AFT; hence, a negative sign on the DM statistic indicates that, on average, BRAND X errors are larger than AFT errors; conversely, a positive sign indicates AFT forecast errors are predominantly greater than BRAND X's errors; when the DM statistic exceeds 1.63, we can conclude with 95% confidence that BRAND X's forecasts are generally more accurate than AFT; conversely, DM values less than -1.63, indicate with 95% confidence that AFT's forecasts are generally more accurate than BRAND X; as the value of the DM falls inside of +/- 1.63, the relative forecasting accuracy of the two models becomes "too close call".

4) R-Square: the proportion of the variation in actual prepayments that are accounted for by the model (derived as a function of the models deviations from actual).

The objective of this note is to demonstrate the application of statistical methods useful for assessing the relative accuracy of competing models' forecast. These methods are empirical in their orientation in that no judgment is made as to how a model's forecast is derived. However, while the analysis necessarily entails evaluating historical forecasts, the forecasts evaluated by the analysis may be temporarily out-of-sample. For example, consider two models that were estimated and put into service, say, two years ago. The methods discussed is this note can be used to evaluate the forecasts made by the model in the most recent two years. Thus, the results of the statistical analysis can be interpreted as an indirect assessment of the performance of the embedded behavioral model. Some standard statistical procedures will be discussed, however, the primary focus is on the Diebold-Mariano (DM) statistic. In essence, the DM statistic compares the forecast errors of two competing models to derive a probable statement as to which model is relatively more accurate.

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The Models and the Data

For purposes of illustration, we conduct a comparative analysis of the forecast accuracy of two mortgage prepayment models: (1) AFT's "Espiel" model and (2) a hypothetical "Brand X" model. For expediency, the analysis is limited to conventional 30-year fixed rate product, and in particular, pools issued by Fannie Mae.

A caveat with regard to assessing forecast accuracy via back testing is in order. Over a period of 10 years, prepayment models undergo revisions and updates to reflect changes in the fundamentals of the prepayment decision. For instance, changes in application processing, technology, and marketing have shortened the lag time for a refinancing by 1-2 months; blitz marketing, among other factors, has heightened borrower sensitivity to refinancing opportunities; and, the overall long-term housing turn over rate is higher than it was 10 years ago. Consequently, it is inappropriate to apply today's models too far back in the past. To mitigate this problem, the retrospective forecasts are limited to five years. Thus, on a pool originated in May 1993, forecasts are restricted to the period November 1998 to the present.

For complete article and statistical results visit *www.aftgo.com/durations.*

Methods and Analysis

The methods used to evaluate forecast accuracy exploit the following observation regarding model structure. Rigorous prepayment models, such as the two evaluated in this study, are non-linear time series models that generate path dependent forecasts. As such, the prepayment forecast for any given month depends on the model's forecast for the immediately preceding month. Thus, the process of producing a lifetime forecast entails generating each monthly forecast in a "one-step ahead" fashion; that is, the model structure requires that the forecasts be generated in sequence from the first month to the final month projected. From the sequential forecasts, a sequence of one-step ahead forecasts *errors* can be calculated: $\varepsilon_{t|t-1} = y_t - \hat{y}_{t|t-1}$, where, y_t the actual CPR for month t, and $\hat{y}_{t|t-1} =$ the forecasted CPR for month t given the predicted CPR at month t-1. For complete article and statistical results visit *www.aftgo.com/durations*.

Below is AFT's prepayment forecast for Fannie Mae 30-year fixed rate mortgages. The next 'Durations' newsletter will include updated AFT forecasts versus actuals.

						Actual (CPR)				Projected (CPR)				Long Term	
Net	Orig Mo/Yr	WAC	WAM	AGE	AMT OUT (Millions)	1yr Av	APR	MAY	JUN	JUL	AUG	SEP	1yr Av	WAL eqv CPR	WAL eqv PSA
4.50	08 2003	5.05	349	11	34,952	2.57	4.84	6.05	6.6	7.01	5.77	4.38	4.75	8.49	152.35
5.00	08 2003	5.49	349	11	227,694	6.51	10.28	15.69	11.8	9.28	7.76	6.0	6.60	9.85	177.42
5.50	11 2002	6.01	340	20	56,698	32.95	31.27	43.49	28.62	22.84	14.45	10.9	11.61	1.81	201.74
5.50	06 2003	5.95	347	13	278,156	19.89	24.33	35.35	22.57	17.73	11.95	9.24	9.98	11.58	206.54
6.00	10 1998	6.64	291	69	9,429	54.81	44.73	49.69	42.05	37.83	23.43	18.63	20.61	7.86	297.59
6.00	06 2003	6.51	347	13	80,020	32.97	39.8	45.56	35.35	27.2	16.42	11.92	14.26	15.63	282.77
6.50	11 1993	7.04	232	128	3,009	50.52	40.46	41.57	38.6	37.11	29.42	19.66	20.58	16.11	268.42
6.50	04 1996	7.16	261	99	1,088	53.46	44.65	45.92	41.80	41.72	35.93	26.72	26.89	20.46	341.03
6.50	08 1998	7.06	289	71	12,189	57.24	48.03	50.12	46.51	45.32	37.6	26.39	27.23	19.74	329.02
6.50	08 2001	7.02	325	35	28,998	60.89	54.55	56.55	51.33	48.55	38.58	26.38	27.4	19.74	328.98
6.50	06 2002	6.98	335	25	37,603	56.28	52.94	56.17	49.3	45.4	35.73	24.22	26.42	19.73	332.09
7.00	08 1993	7.51	229	131	3,390	50.85	41.26	41.94	40.14	37.16	35.53	32.36	29.17	20.76	345.94
7.00	05 1996	7.6	262	98	1,587	52.06	44.5	44.92	44.78	41.55	39.36	35.98	32.68	23.09	384.76
7.00	07 2001	7.56	324	36	10,713	57.86	53.71	53.61	50.99	48.36	46.65	43.01	38.94	26.07	434.47
7.00	05 2002	7.52	334	26	10,370	54.48	53.58	53.83	51.68	48.12	46.57	43.54	40.22	27.24	458.15
7.50	06 1993	7.95	227	133	1,100	48.13	40.66	39.39	38.12	36.87	36.12	33.37	29.24	20.41	340.19
7.50	07 1996	8.09	264	96	1,302	48.86	45.24	42.04	41.47	38.98	38.51	35.96	31.74	22.27	371.21
7.50	10 1999	8.0	303	57	1,974	53.83	49.6	44.58	45.01	43.15	42.68	40.27	35.82	24.06	400.93
7.50	06 2002	8.12	335	25	1,761	55.37	55.30	55.80	53.01	50.4	49.27	46.37	41.51	27.28	460.67
8.00	07 1992	8.54	216	144	1,028	44.22	39.46	34.14	33.91	34.52	34.06	31.66	27.84	19.91	331.8
8.00	07 2000	8.6	312	48	2,212	53.48	49.73	48.14	46.93	44.57	43.59	40.66	35.57	23.65	394.14

Base Rates	30 year rate:	6.25
	15 year rate:	5.59

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In this issue:

Intelligent, accurate.

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