QUANTITATIVE PERSPECTIVES

DIVIDE & CONQUER: EXPLORING NEW OAS HORIZONS

PART I: ACTIVE-PASSIVE DECOMPOSITION

by Alex Levin

October 2003

ANDREW DAVIDSON & CO., INC.

DIVIDE & CONQUER: EXPLORING NEW OAS HORIZONS

PART I: ACTIVE-PASSIVE DECOMPOSITION

by Alex Levin

October 2003

QUANTITATIVE PERSPECTIVES

Introduction

In two previous publications (Levin [2001, 2002]), a new method of mortgage valuation modeling called active-passive decomposition (APD) was introduced. An efficient alternative to brute-force Monte-Carlo, the APD method splits a mortgage pass-through into two path-independent components, the active (refinancable) and the passive (non-refinancable). Once this is done, the most time-efficient pricing structures operating backwards on probability trees or finite-difference grids can be employed. This valuation method runs faster than Monte-Carlo while delivering a much richer outcome -- all stressed values required by mandatory risk assessments -- at no additional cost. Risk managers and traders of unstructured mortgage instruments, such as agency pass-through MBS, whole loans, stripped (IO/PO) derivatives, including mortgage servicing rights (MSRs) may directly benefit from the method.

The APD approach simulates the burnout effect in a natural and explicit way - through modeling the heterogeneity of the collateral. Hence, it presents an analytical advantage over any other approach that requires ad-hoc judgments about the achieved degree of burnout. Structured instruments, CMOs and ABS, though they retain heavy sources of path-dependence (other than the burnout) and still rely on Monte-Carlo pricing, can gain from a better, more robust prepay modeling.

The multi-population view of mortgage collateral is a known approach to explain the burnout effect. In one of the earliest modeling attempts, Davidson [1987] and Davidson et al [1988] proposed the Refinancing Threshold model in which collateral is split into three or more American option bonds having differing strikes. A conceptually similar approach proposed recently by Kalotay and Young [2002] divides collateral into bonds differing by their exercise timing. Such structures naturally call for the backward induction pricing, but they fall short in replicating actually observed, probabilistically smoothed prepayment behavior - even if many constituent bonds are used. On the other hand, contemporary analytical systems used by the Street often employ multi-population mortgage models (see Hayre [1994, 2000]), but do not seek any computational benefits, as they rely heavily on Monte-Carlo pricing anyway.

The APD is a "mortgage-like" model, with a refinancing S-curve, aging, and other ad-hoc features that are meant to capture non-efficient, empirical option exercise. Therefore, it is capable of generating realistic prepayment behavior with only two constituent components, the active and the passive. We will give an overview of the extended APD model in Part I of this *Quantitative Perspectives* series. In this extended model, we allow passive mortgagors to be partial refinancers, albeit at a reduced speed. Such an extension, while not elevating technical complexity of the model, leads to a better historical fit, especially for very burnt pools.

Because the model relies on the backward induction valuation performed separately for its two components, it naturally assesses their future prices - very much unlike Monte-Carlo. It sets an analytical framework where both valuation and prepayments can be modeled rigorously, beyond the traditional OAS framework. We will present an elegant CAPM-like mortgage valuation model in the Part II of this series. In this model, armed with the power of backward induction, we endogenously find prepay risk measures and the price of risk in the form of return spread compensation for each investment period and level of interest rates. A value thus obtained, therefore, will carry financially well-defined return demand and may operate without an exogenous OAS input. The entire valuation model implemented on the same probability tree or finite-difference grid will deliver objective economic measures (price, OAS, duration, convexity, option cost, etc.) from a sector-wide spread measure, such as the agency debt spread. For example, values for IOs, POs and MSRs can be objectively derived without knowing the differences in OAS; OAS, in fact can be calculated from these economic values once they are determined.

Path-dependence & Pricing PDE

Let us consider a hypothetical dynamic asset ("mortgage") market price of which $P(t,x)$ depends on time t and a single market factor x. The latter can be formally anything and does not necessarily have to be the short market rate or the yield on the security analyzed. We treat $x(t)$ as a random process having a (generally variable) drift rate μ and a volatility rate σ and being disturbed by a standard Brownian motion $z(t)$, i.e.

$$dx = \mu dt + \sigma dz \qquad (1)$$

We assume further that the asset continuously pays the $c(t,x)$ coupon rate and its balance B gets amortized at the $\lambda(t,x)$ rate, that is $\frac{\partial B}{\partial t} = -\lambda B$. One can then prove that the price function $P(t,x)$ should solve the following partial differential equation (PDE):

A derivation of this PDE can be found in Levin [1998], but it goes back at

$$\underbrace{r + OAS}_{\text{expected return}} = \underbrace{\frac{1}{P}\frac{\partial P}{\partial t} + \frac{1}{P}(c+\lambda) - \lambda}_{\text{time return}} + \underbrace{\frac{1}{P}\frac{\partial P}{\partial x}\mu}_{\text{drift return}} + \underbrace{\frac{1}{2P}\frac{\partial^2 P}{\partial x^2}\sigma^2}_{\text{diffusion return}} \qquad (2)$$

least to F. Fabozzi and G. Fong [1994]. A notable feature of the above written PDE is the absence of the balance variable, B. The entire effect of possibly random prepayments is represented by the amortization rate function, $\lambda(t,x)$. Although the total cashflow observed for each accrual period does depend on the beginning-period balance, construction of a finite difference scheme and the backward induction will require the knowledge of $\lambda(t,x)$, not the balance. This observation agrees with a trivial practical rule stating that relative price is generally independent of the investment size.

Pricing PDE (2) can be solved on a probability tree or finite difference pricing grid that has as many dimensions as the total number of factors or state variables that affect r, c, and λ. In particular, if the coupon rate is fixed, and the amortization rate λ depends only on current time (loan age) and the immediate single market factor x, the entire valuation problem can be solved backwards on a two-dimensional (x,t) lattice. To implement this method, we would start our valuation process from maturity T when we are sure that the price is par, $P(T,x)=1$, regardless of the value of factor x.

Working backwards, we derive prices at age t-1 from prices already found at age t. In doing so, we replace derivatives in PDE (2) by finite difference approximations, or weigh branches of the lattice by explicitly computed probabilities. If the market is multi-factor, then x should be considered a vector; the lattice will require more dimensions. Generally, the efficiency of finite-difference methods deteriorates quickly on high-dimensional grids because the number of nodes and cash flows grow geometrically; probability trees may maintain their speed, but at the cost of accuracy, if the same number of emanating nodes is used to capture multi-factor dynamics. If we decide to operate on a probability tree instead of employing a finite-difference grid, then for every branch:

$$P_k = \frac{c_k + P_{k+1} + l_k(1 - P_{k+1})}{1 + r_k + OAS} \tag{3}$$

where P_k is the previous-node value deduced from the next-node value P_{k+1}. Probability weighting of thus obtained values applies to all emanating branches.

Extended Active-Passive Decomposition Model

The Concept

Even for a simple fixed-rate mortgage pass-through, total amortization speed λ cannot be modeled as a function of time and the immediate market. Prepayment burnout is a strong source of path-dependence because the future refinancing activity is affected by past incentives. One can think of a mortgage pool as a heterogeneous population of participants having different refinancing propensities. Some mortgagors have higher rates, better credit, larger loans, or perhaps they face smaller state-enforced transaction costs. Once they leave the pool, the future prepayment activity gradually declines.

Instead of considering pricing PDE for the entire collateral, we propose decomposing it first into two components, "active" and "passive", differing in refinancability. Under the following two conditions, mortgage path-dependent collateral can be deemed a simple portfolio of two path-independent instruments:

(A) Active and passive components prepay differently, but follow the immediate market and loan age.

(B) Any migration between components is prohibited.

The Details

Here is an example that fits the above criteria:

$$\begin{aligned}\text{ActiveSMM} &= \text{RefiSMM} + \text{TurnoverSMM}\\ \text{PassiveSMM} &= \beta^*\text{RefiSMM} + \text{TurnoverSMM}\end{aligned} \tag{4}$$

where RefiSMM denotes active speed and TurnoverSMM is the turnover speed, both are assumed to depend on market rates and loan age only. Parameter β quantifies relative refinancing activity for the passive component; it takes values between 0 and 1.

In order to find the total speed, we have to know the collateral composition. Denote ψ the ratio of active group to total, then

$$l \equiv \text{TotalSMM} = \psi^*\text{ActiveSMM} + (1 - \psi)^*\text{PassiveSMM} \tag{5}$$

All variables are time-dependent, but we omitted subscript t for simplicity. The initial value of ψ describes composition of collateral at origination; both ψ_0 and β are parameters for a particular prepay model. Dynamic evolution of ψ from one time moment (t) to the next ($t+1$) is as follows:

$$y_{t+1} = y_t \frac{1 - ActiveSMM_t}{1 - TotalSMM_t} \tag{6}$$

It is worth considering a few special cases. First, if ψ is zero at any instance of time, it will remain zero for life. Second, if ψ is 1 at any time, then it will retain this value as well because TotalSMM is identical to ActiveSMM from equation (5). Indeed, if the mortgage pool is either totally passive ($\psi=0$) or totally active ($\psi=1$), it will retain its status due to complete absence of migration. In either of these two special cases, variables ψ and TotalSMM are path-independent, leading us to a key conclusion: considering active and passive components separately avoids the problem of path-dependence altogether.

How the Model Works Forward

If $0<\psi<1$, then TotalSMM < ActiveSMM, the fraction in the right-hand side of formula (6) is less the 1, and ψ gradually falls. If we employed the APD model for prepay modeling while using Monte-Carlo for valuation, we could innovate the compositional variable ψ month after month. First, we would compute refinancing and turnover speeds at time *t* from their respective models. Then, we would produce active, passive and total speeds, all still at time *t*, from formulas (4) and (5). This information is sufficient to generate the *t*-month cash flow and also allows for finding the next-month composition, ψ_{t+1}, from formula (6) and proceed forward.

Note that prepay speeds RefiSMM and TurnoverSMM depend only on current market rates and time, i.e. they are path-independent. Naturally, ActiveSMM and PassiveSMM found from (4) will be path-independent as well. In contrast, variables ψ and TotalSMM are generally path-dependent -- except when ψ is either 0 or 1.

Let us look at how the APD model works. Suppose we have a pool with $\psi_0=0.8$, i.e. the active part constitutes 80% of total, at origination. Consider two possible scenarios: (A) rates drop and remain low inducing refinancing activity, and (B) rates rise and remain high. Figures 1A & 1B show how the pool composition will evolve in these two cases.

Figure 1A: Rate Decrease (refinancing wave)

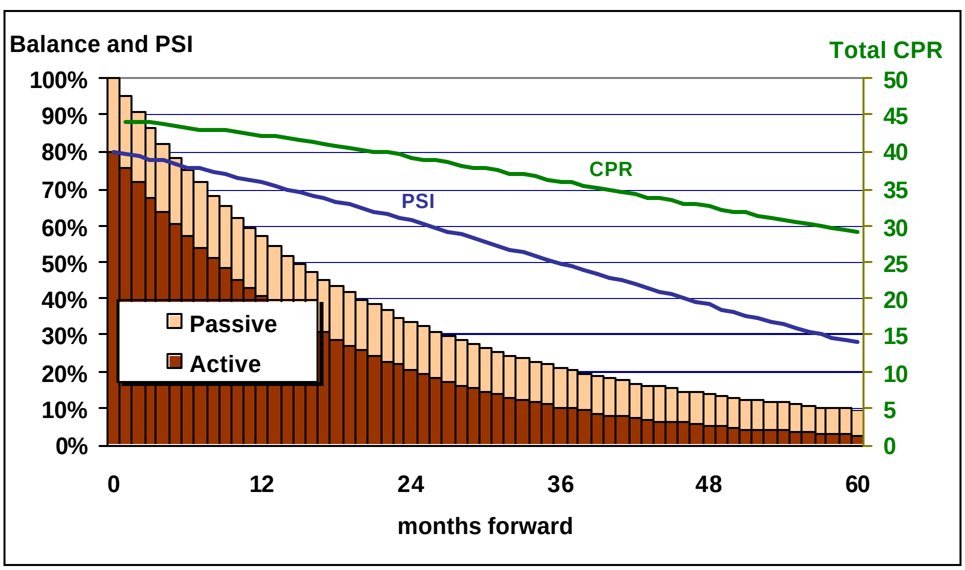
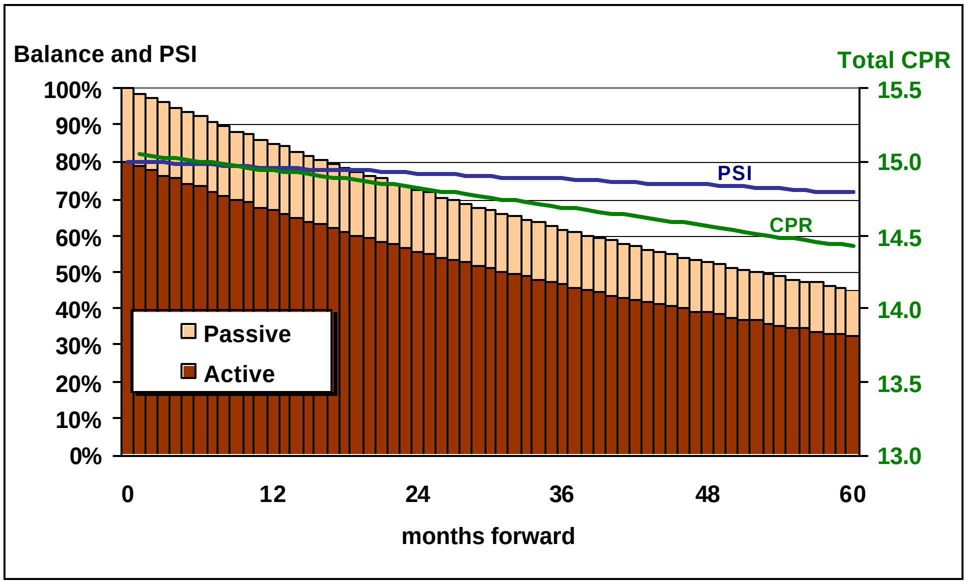


Figure 1B:

Rate Increase



For scenario (A), pool balance gets amortized quickly due to the refinancing wave, but, more importantly, the active group (brown bars) evaporates much faster than the passive group (beige bars). As a result, variable ψ (blue line) drops from the original 80% to under 30%, and, correspondingly, the total speed (green line) declines -- in the complete absence of any rate dynamics. A sizable speed reduction from 45 CPR to 30 CPR is caused exclusively by the burnout effect and reflected by ψ. This effect is not seen on Figure 1B, where the active and the passive groups retire at similar rates. Pool composition barely changes, as does the total prepayment speed.

We could give prepayment behaviors seen in Figures 1A and 1B another interesting practical interpretation. Let us assume that we wish to compare a regular fixed-rate pool (Figure 1A) with a prepayment-penalty pool (Figure 1B) under the same, low-rate market conditions. The regular pool burns out -- unlike the prepay-penalty one, which faces additional refinancing barrier. At the end of its penalty window (assume 60 months), this pool retains a relatively high level of ψ (71.7%). Looking at a matching speed level in Figure 1A, we conclude that, once the penalty window is over, the prepay speed will jump above 40 CPR (compared to 29 CPR of the regular pool). Therefore, the APD model naturally explains the "catch-up" effect actually known for prepay-penalty mortgages.

Above, we assumed a newly originated pool, the population of which is determined by parameter ψ_0. In practice, a pool may be already seasoned, and today's value of ψ, denote it $\psi(t_0)$, needs to be determined first. We will cover this task shortly.

How the Model Works in Backward Induction

If we decide to employ the APD model for backward valuation, we do not need to innovate path-dependent variables, ψ and TotalSMM, or keep track of their dynamics. Below are a few simple steps to perform:

Step 1 Recover today's value of the population variable, $\psi(t_0)$.

Step 2A Generate cash flows on each node of a pricing grid (tree) for the active part only, and value it using a backward inducting scheme that solves pricing equation (2).

Step 2B Do the same for the passive part.

Step 3. Combine thus obtained values as:

$$P = y\,(t_0) P_{active} + [1 - y\,(t_0)] P_{passive} \tag{7}$$

Interestingly enough, formula (7) applies to today's prices obtained for all interest rate levels of the pricing grid. As stated above, computing prices on the entire grid is an inseparable part of backward valuation. Therefore, the total price can be also found on the grid at no additional cost.

In particular, the Greeks (e.g., durations, convexity) are found immediately, without any repetitive efforts with stressed market (compare with Monte-Carlo!) However, we cannot apply formula (7) for future nodes because we know only $\psi(t_0)$ - today's value of ψ.

Initializing the Burnout Factor

If the pool is already seasoned, we have to assess $\psi(t_0)$ first before we can employ the APD model either for forward simulation or backward induction. Two main approaches may be employed to solve this problem, an analytical closed-form method, or historical simulations.

Let us suppose we know the pool's age, t_0, factor, $F(t_0)$, and a constant turnover rate[1], $\lambda_{turnover}$. We can then assess the turnover factor $F_{turnover}(t_0)=\exp(-\lambda_{turnover} t_0)$ along with the scheduled factor, $F_{scheduled}(t_0)$. Since the entire pool's amortization is driven by refinancing, turnover, and the scheduled payoff, knowing two out of three factors along with the total pool's factor is enough to restore the entire time t_0

[1]We can relax this condition by assuming turnover rate is known, not necessarily constant.

composition. It is easy to show that unknown $x = \psi(t_0)$ satisfies the following, generally transcendent, algebraic equation:

$$x + a x^{b} = 1 \qquad (8)$$

where α is a known parameter:

$$a = \frac{1 - y_0}{y_0^{b}} \left[\frac{F_{turnover}(t_0) F_{scheduled}(t_0)}{F(t_0)} \right]^{1-b}$$

and β is the same speed-reducing multiplier that enters the APD model (4).

Of course, no numerical iterations are needed if β is 0, 1, or 0.5. For instance, β=1 is a trivial case when the pool is homogeneous and is not subject to burnout, $\psi(t_0)=\psi_0$. Case β=0 was considered in Levin [2001, 2002]; it leads to:

$$y(t_0) = 1 - (1 - y_0) \frac{F_{turnover}(t_0) F_{scheduled}(t_0)}{F(t_0)}$$

A simple quadratic equation for $\psi(t_0)$ arises when β=0.5, with only one meaningful positive solution. For all other values of β, numerical methods will suffice.

Solving equation (8) is an attractive way to initialize the burnout stage, as it does not require a historical simulation of past refinancing incentives. However, it is valid only for the very specific form of the APD model presented by formulas (4) and (5). Any possible extension of the model (such as discussed below) will make it impossible to recover the burnout stage using the pool's factor and age information, only. An alternative method to estimate $\psi(t_0)$ would be a historical simulation of all prepayment components, i.e. running the APD model forward, from a pool origination until today. A relevant historical interest rate database will be required to facilitate this process, which constitutes the essence of AD&Co.'s data files currently distributed to clients, monthly.

Extensions & Nuances

More components, more prepay sources

The APD model (4)-(6) is a two-component pool model exposed to two sources of prepayment, refinancing and turnover. Each of these features prepayment patterns (super-active, active, moderately active, etc.). On the other hand, there may exist prepayment sources that contribute to each of the groups, but are distinctly different from refinancing and turnover. Let us briefly review both ways to extend the model.

As we already pointed out, even a two-component model ensures smooth prepayment behavior if each component does so. Within our APD framework, a refinancing model may include a traditional S-like curve, aging and perhaps some other known empirical mortgage effects that can be attributed to a non-optimal option exercise. The total prepayment speed is proven to be between RefiSMM and TurnoverSMM, being continuously weighted as controlled by variable $\psi(t)$. Adding more components into the model does not alter this fact, nor does it add any smoothness to the prepay model. It is also more difficult to fit a three- or four-component model than the APD model presented here.

The APD model (4), (5) assumes that the active and passive components share the same turnover rate, and their refinancing speeds relate to one another as 1 to β. We can consider some other prepayment source that is not propagated to the active and passive components identically, or with the 1 to β ratio. For example, we may introduce a credit cure prepay source, additional to refinancing and turnover, but likely having higher effect on the passive part than on the active part. The cash-out refinancing driven by home prices carries a similar effect.

Of course, additional prepayment sources can be formally included in the refinancing without assuming any longer that active and passive refinancing models relate to one another as 1 to β. We will not be able to initialize $\psi(t_0)$ by solving equation (8), and we must use historical simulations for this purpose as discussed above. Principally, we may assume unrelated refinancing models built for the active and passive components, gaining generality with little sacrifice of convenience.

Modeling Refinancing Speed as a Function of Price

Having asserted that the APD model is a "mortgage-like" model, we mean to distinguish it from the other popular academic approach, the rational prepayment exercise models (see Longstaff [2003], Stanton [1995]). Yet, the APD model can address some shortcomings typically known for purely ad-hoc experimental models. As we have already affirmed, the APD model can value MBS backward, provided that its refinancing and turnover constituents depend only on the current market. A likely implementation of this rule would rely on some experimental relationship between the SMMs and a relevant mortgage index. Although this is the way most mortgage practitioners envision prepayment modeling, it is not the only possible approach. In fact, refinancing behavior of homeowners also depends on the type of mortgage in hand. Given the coupon and market, economic incentive to prepay vanishes when maturity, balloon or ARM reset approach.

An attractive alternative would be linking refinancing speeds of a mortgage (still measured on the grid nodes, separately for the active and passive pieces) directly to its price appreciation using path-independent specification RefiSMM(Price) instead of RefiSMM(Rate). This is the same approach used for the valuation of American option bonds, except the refinancing model can still be an experimental S-curve, not the "optimal" or "rational" exercise rule. This model would state the refinancing speed, RefiSMM, as a function of price premium, for example, 2 SMM if collateral is priced at 102, 6 SMM for 104, etc., asymptomatically approaching its "ultimate" speed. Formulas (4), (5) still allow for computing the active, passive, and total speeds. In particular, the passive component will still refinance at a beta-reduced speed for the same price premium as the active component.

Such a refinancing model will still be path-independent, presenting no theoretical or computational issues for the backward valuation. Moreover, if the refinancing behavior is indeed driven by price appreciation and such a universal relationship can be experimentally established, then the APD modeling approach and its backward implementation becomes a natural, if not only, way to price an MBS. In contrast, Monte-Carlo-based valuation method simply would not allow assessing future prices and, hence, prepayment speeds.

Arguably, the RefiSMM(Price) function can be viewed as one universal refinancing rule that can serve many collateral types. Furthermore, such a model can directly account for additional, loan-specific, transaction cost and cost-saving opportunities. For example, the knowledge of prepayment penalties, average loan sizes, or state-imposed taxes can easily be used to modify the S-curve.

Valuation Features of Mortgage Servicing Rights (MSR)

FAS 133 regulation has increased the practical importance of quick yet rigorous valuation of MSR. Now, managers of MSRs have to mark to market their assets often and monitor values against fairly complex hedges, both mandatory and optional. As explained in Levin [2002], MSR can benefit from the use of the APD model. Here is the main argument.

MSR are different from an IO in that they carry some fixed (non-proportional) dollar income and cost components counted per loan. For example, a mortgage servicer may receive an annual $40 per loan in the form of ancillary income (floats, insurance fees, etc.) -- regardless of the loan size. It is clear that the proportional rate c used in pricing PDE (2) will now change gradually with the average loan balance, even if the stated servicing spread is constant. Does the existence of non-proportional income or cost create path-dependence?

Consider the following simple transformation of the fixed dollar income (or cost):

$$\text{Income per \$1 of balance} = \text{Income per loan} / \text{Average loan balance} \quad (9)$$

Income per loan is fixed for fixed-rate loans, whereas the average loan balance gradually amortizes. The only two sources of a particular loan's amortization are the scheduled payments and curtailments (refinancing or turnover would eliminate the loan immediately). Since the scheduled amortization is market-independent at least for fixed-rate mortgages, we arrive at the following practically important conclusion: in order to apply the APD model for MSR, we have to assume that the curtailments are rate-independent.[2] This conjecture makes fixed dollar income or cost path-independent. The rest of the MSR valuation is no different from regular unstructured pass-throughs and can be carried over using pricing methods employed for the active component and the passive component, as explained above.

Residual Sources of Path-Dependence

The APD model takes care of the burnout effect, the major source of path-dependence for fixed-rate mortgages. After the decomposition is done, we

[2] Although curtailments are rate-dependent in practice, the entire curtailment speed does not exceed 1-2 CPR, for most pools. Prepayment penalties may be a counter-example.

need to review residual sources of path-dependence and arrange the numerical valuation procedure such as to reduce or eliminate potential pricing errors.

Prepayment lag, a lookback option feature, is such a source. Applications to obtain a new mortgage replacing an old one enter the origination pipeline 30-90 days before the loan is actually closed and the existing debt is paid off. Even if the prepayment model features a lag, but the backward valuation scheme is unaware of its existence, the pricing results can be somewhat inaccurate. This ignorance of the lag by the backward induction scheme usually causes small errors for pass-throughs. However, mortgage strip derivatives and MSR are highly prepayment-sensitive, and the lag may change their values in a sizable way.

It is generally known that lookbacks with fairly short lag periods can be accounted for while running the backward induction process. Let us assume, for example, that on a trinomial monthly tree speed λ_k actually depends on market rates lagging 1 month. Hence, the MBS value will also depend on both the current market and 1-month lagged market. This is to say that each valuation node of the tree should be "sliced" into 3 sub-nodes keeping track of prices matching 3 possible historical nodes 1 month back. Of course, this costs computational time; efficiency may deteriorate quickly for deeper lags and more complex trees.

Approximate alternatives do exist and it is feasible to reduce pricing errors without much trouble. AD&Co. employs a progressively sparse pentanomial tree, which does not branch every month. Branches of the tree are made from 2 to 12 months long so that the lagged market rates are explicitly known for most monthly steps. The lookback correction can also be adapted for "fractional" prepayment lag that almost always exists due to the net payment delay between the accrued-month-end and the actual cash flow date. In such a case, λ_k could be interpolated between the current-month and the previous-month values. Thus, the total lookback processing should account for both prepay lag and payment delay.

Another example of path-dependence not cured by pool decomposition is oupon reset for ARMs. Both reset caps and nonlinear relationships between the prepayment and coupon make it difficult for a backward induction scheme to account for this feature. One possible solution is to extend the state space and create an additional dimension that would keep track of the ARM coupon rate (Dorigan et al. [2001]). This state space extension will come at a cost of both computational efficiency and memory consumption. Our other study (Levin [2002]) suggests that the reset provisions found in typical ARMs allow for backward valuation with OAS accuracy within 4-5 bps, without any special measures on curing this path-dependence, under a normal term structure model. Backward valuation of ARMs remains a subject of further research.

Conclusion

The active-passive decomposition model naturally simulates the burnout and other prepayment effects, such as incentive-dependent speed ramping or "catch-up" for prepay-penalty pools. For pass-throughs and their strip derivatives, including MSRs, it splits valuation into two quick backward induction steps and produces an entire pricing grid for risk measurement at no additional cost (unlike Monte-Carlo). Whereas CMOs will still rely on Monte-Carlo as being heavily path-dependent beyond the burnout, they could benefit from better prepay modeling.

Finally, the ability to employ the backward induction pricing technique makes future values accessible, which, in itself, opens doors to new valuation and modeling tasks. We will demonstrate this interesting point in Part II of this *Quantitative Perspectives* series.

■

Acknowledgements

The extended APD model presented in this paper has greatly benefited from joint work with Andrew Davidson. The author is grateful to Jay Delong who successfully integrated the model into the newly developed ADCO valuation system. He also wishes to thank Dan Szakallas for tuning and optimizing the model to historical prepay data, Will Searle for the model implementation in a C++ library, and Ilda Pozhegu for her diligent publishing work.

A. Davidson, Understanding Premium Mortgage-Backed Securities: Observations & Analysis, in F. Fabozzi (ed.), *Mortgage-Backed Securities: New Strategies, Applications & Research*, Probus Publishing, Chi, 1987, pp. 191-204.

A. Davidson, M. Herskovitz, L. Van Drunen, The Refinancing Threshold Model: An Economic Approach to Valuing MBS", *Journal of Real Estate Finance and Economics 1*, June 1988, pp. 117-130.

M. Dorigan, F. Fabozzi, and A. Kalotay, Valuation of Floating-Rate Bonds, in F. Fabozzi (ed.), *Professional Perspectives on Fixed Income Portfolio Management*, vol. 2, Frank J. Fabozzi Associates, New Hope, PA, 2001.

F. Fabozzi and G. Fong, *Advanced Fixed Income Portfolio Management*, Irwin Professional Publishing, 1994.

L. Hayre, A Simple Statistical Framework for Modeling Burnout and Refinancing Behavior, *The Journal of Fixed Income*, Dec. 1994, pp. 69-74.

L. Hayre, Anatomy of Prepayments, *The Journal of Fixed Income*, June 2000, pp. 19-49.

J. Hull, *Options, Futures, and Other Derivative Securities*, 2nd (or later) edition, Prentice Hall, 1996.

A. Kalotay and D. Young, An Implied Prepayment Model for Mortgage-Backed Securities, presentation at the Bachelier Congress, Crete, 2002.

A. Levin, Deriving Closed-Form Solutions for Gaussian Pricing Models: A Systematic Time-Domain Approach, *International Journal of Theoretical and Applied Finance*, 1(3), 1998, pp. 348 - 376.

A. Levin, Active-Passive Decomposition in Burnout Modeling, *The Journal of Fixed Income*, March 2001, pp. 27-40.

A. Levin, Mortgage Pricing on Low-Dimensional Grids, chapter 18, F. Fabozzi (ed.), *Interest Rate, Term Structure, and Valuation Modeling*, Wiley Finance, 2002, pp. 469-488.

F. Longstaff, Optimal Recursive Refinancing and the Valuation of Mortgage-Backed Securities, in *Derivatives 2003: Reports from the Frontiers*, NYU/Stern Conference proceedings (book 2), 2003.

R. Stanton, Rational Prepayments and the Valuation of Mortgage-Backed Securities, *The Reviews of Financial Studies*, 8, 1995, pp. 677-708.

About the Author

Alex Levin *is a Senior Quantitative Developer/Consultant responsible for the research and development of analytical models for mortgages and other financial instruments and related consulting work. Alex has developed a suite of interest rate models that can be calibrated to swap rates and a swaption volatility matrix. He also leads Andrew Davidson & Co., Inc.'s efforts in developing new efficient valuation models, including the Active-Passive Decomposition (APD) mortgage model facilitated by a backward induction OAS pricing, and carries out research on prepay risk- and option-adjusted valuation that allows for objective pricing without an OAS input.*

Until March of 2002, Alex was a Senior Vice President and Director of Treasury Research and Analytics at The Dime Bancorp (the Dime) in New York. At the Dime, he was in charge of developing efficient numerical and analytical tools for pricing and modeling mortgages, options, deposits, and other complex term-structure-contingent derivatives, risk measurement and management. He has authored Mortgage Solutions, Deposit Solutions and Option Solutions, the Dime's proprietary pricing systems that were intensively used for both security trading and risk assessment. In addition, he was regularly involved in measuring market risk (including a counter-party value-based risk) and hedging positions in various lines of the banking business.

Prior to his employ at the Dime, Alex taught at The City College of NY and worked at Ryan Labs, a fixed income research and money management company.

Alex is a regular speaker at the Mathematical Finance Seminar (NYU, Courant Institute), Andrew Davidson & Co., Inc. conferences, and has published a number of papers. He holds an M.S. in Applied Mathematics from Naval Engineering Institute, Leningrad and a Ph.D. in Control and Dynamic Systems from Leningrad State University.

ANDREW DAVIDSON & CO., INC.
520 BROADWAY, EIGHTH FLOOR
NEW YORK, NY 10012
212•274•9075
FAX 212•274•0545
mail@ad-co.com

Quantitative Perspectives is available via
www.ad-co.com

We welcome your comments and suggestions.

ANDREW DAVIDSON & CO., INC.