VALUATION OF AGRICULTURAL LOAN GUARANTEES

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Introduction

Government programs guaranteeing loans and the cash flows associated with mortgage securities are often justified by the argument that the sum of the benefits accruing from the guaranteed activity are greater than the cost of the guarantee, but are less than the value of the privately accruing benefits (Ho and Singer; Jones and Mason). The most prominent examples are found in secondary mortgage markets for residential real estate, but numerous other government guarantees on loans and related instruments exist including programs involving agricultural mortgages, foreign loans supporting exports, pension benefit guarantees, deposit insurance, and so on. GAO estimated in 1993 that the total face value of explicit federal government guarantees was over $660 billion, with several hundred billion dollars additional of implicitly-backed obligations. Although the share committed to agricultural concerns is a relatively small fraction of the total, its aggregate size is still substantial and could continue to increase in the future as the government continues to de-emphasize direct lending programs in favor of guaranteed and insured loan programs.[2]

Beginning in 1992, the Credit Reform Act (PL 101-508) required that the expected present value of guaranteed loan programs be recorded in the budget as an expense. Since then, however, little consensus has been reached as to the appropriate approach for formulating those estimates. This study examines the issue of guarantee valuation in the context of agricultural mortgage lending. The resolution of this issue is of particular interest to several participants in agricultural credit markets including the Federal Agricultural Mortgage Corporation (Farmer Mac), its regulator -- FCA, policy makers, taxpayers, and potential customers and sellers in the developing secondary market for agricultural mortgages. The relevance of the study to these participants is briefly elaborated in what follows.

Farmer Mac recently recieved regulatory relief that permits it to operate in a mode that is similar to the GSEs providing secondary markets for rural housing loans. Their new

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[2]Direct shares are not attributable to specific sectors in the GAO report, but commitments to agriculture through CCC and FSA programs alone total over $19 billion (USDA-ERS).

authorities could result in significant changes in both the nature of risks borne and the location at which the risks are experienced. The net effect of these changes is that Farmer Mac now has the authority and intent to behave as an issuer of insurance against credit losses in pools of agricultural mortgages. Thus, guarantees provided by Farmer Mac now differ substantially from those offered under previous authority -- those which were generally thought to pose little or no exposure to credit risk in excess of the subordinated participation interest.

Under the new structure, there is an increased need to develop capacity to conduct formal credit risk assessment and to develop accurate expectations about the value of the guarantees issued. Specific applications by Farmer Mac may include: (i) evaluation of new business opportunities, (ii) monitoring of existing portfolio loss exposure and development of appropriate reserve policy, (iii) evaluation of underwriting standards and their relationships to guarantee fees, (iv) evaluation of adequacy/profitability of alternate guarantee fee structures and/or negotiated rates in specific circumstances; (v) monitoring and control over the origination and servicing functions by loan originators, and possibly other areas. In each case, there is a direct need to assess the credit risk exposure to Farmer Mac arising from guarantees issued on pools of loans.

Other parties are likewise more in need of an accurate understanding of the actuarial characteristics of agricultural and related loan guarantees. The government's contingent exposure is derivative of the valuation of the guarantee and overall performance of the agency issuing the guarantee. Likewise, government agency regulators such as FCA need to have an accurate understanding of the loss behavior of pooled agricultural loans to assess the performance and soundness of the institution issuing the guarantees. Banks and other potential customers have to evaluate the desirability of the guarantee in conjunction with the exchange or sale of assets with Farmer Mac, although many other items affect the value of securitization for potential loan sellers. Finally, academics predicting success or failure ahead of the market's demonstration, are interested in developing an accurate conceptualization of the guarantee, and assessing potential performance in practice.

This report focuses on pool-level insurance concepts and the probabilistic features of loss exposure arising from guarantees issued against pools of agricultural mortgages. It is thus concerned only with the credit-risk portion of the value of a guarantee and does not address the ancillary components that, in additional to the actuarial characteristics of the guarantee, determine feasibility of a guarantee program and its desirability in a policy context. Concentration on the credit-risk aspect alone is justified in that the insurability dimension of the pooled risks is the first necessary, although not sufficient, characteristic for successful development of a secondary market in agricultural loans. The remainder of the features that will determine the overall performance of the guarantees are more firm specific and dictated by behavior of the participants, and while intriguing, are not the point of this report.

To address the purposes of this paper, a simulation model is used that permits flexibility to change broad underwriting standards and pool composition characteristics in order to examine a wide variety of economic conditions and underwriting standards. Required inputs include loan origination information and as much loan performance data as are available (more detail about the data requirements is provided later). This report utilizes specific loan level historic data originated within the Farm Credit Banks of Texas and St. Paul. However, the approach can and should accommodate other sources of data as they become available.

The output of the model is in the form of pool-level loss distributions conditional on data and user inputs. Against this probabilistic information, alternate guarantee fee values can be related to their likelihoods for exhaustion. Alternatively, any particular tolerance for insolvency can be associated with the size of a guarantee fee, or price of insurance against those losses. Thus, the model employed translates a set of loan-level risk measures into a pool-level insurance exposure measure for the purpose of evaluating guarantee adequacy and other business operations related to the guarantee stream income.

Insurance Concepts and Modeling Considerations

Credit risks of individual loans depend on a host of firm specific conditions, macro-economic conditions, crop markets, geographic variations in weather, government actions, and so on. The relationships among these variables and eventual loan performance are both imprecise and complex. Because *ex ante* loan performance is a probabilistic concept, and because the distribution of possible outcomes is difficult to characterize based on origination information alone, minimum qualification underwriting standards are frequently employed by lenders to broadly classify loans with varying likelihoods for performance. Ideally, the set of loans available for pooling could be distinguished between those with higher and lower likelihoods for default. However, because the nature and causes of defaults are not entirely dependent on initial observable conditions, eligibility screens cannot fully identify default risk. For an accurate understanding of the pool-level risks that remain after unqualified loans are screened out, the probabilistic information contained in the basic exposure units (loans) must be retained in a manner to permit the composite loss distribution (pools) to be recovered. The necessary characterizations of each are discussed below.

Loan Level information

Credit risk assessment at the loan level involve two types of efforts. First, impacts of changes in the initial conditions, underwriting variables, and terms of the loan on the probability of default can be investigated. This line of inquiry is the basic thrust of credit scoring efforts -- to understand how changes in variables that can be observed at origination affect the loan performance. Understanding how changes in initial borrower conditions and loan terms affect the outcomes provides a loss-probability distribution for loans with particular initial conditions and terms. Depending on the nature of these distributions, inferences can be made with varying strength about the eventual performance of a particular loan.

The second type of effort focuses on characterizing the nature of these conditional loan performance distributions. The loss distributions at the loan level can be further described according to: (i) severity -- the size of loss given that a loss occurs, (ii) frequency -- the likelihood that a certain number of loans will default, and (iii) timing -- when in the life of a loan a loss occurs.

Pool Level information

As loans are pooled, the pool loss exposures may change from that of its components. Under ideal pooling conditions, the aggregate losses are predictable even though the (individual loan) specific sources of loss may not be. Consider the following analogy: if we were to flip 1000 coins, we can predict that approximately one-half will turn up heads even though we could not identify which particular coins would be heads ahead of time. We could, however, describe the probability distribution for outcomes as {heads = ½, tails = ½} for each coin ahead of time. Further, we can compute the likelihood of, say, flipping more than 650 heads out of 1000 from knowledge about the probability measures for the individual coins.

With less precise information, or if more variable probability measures are encountered, aggregate outcomes become more difficult to predict. Interaction among the units, and influence from outside forces complicate probability assessments for joint outcomes. For pooled loans, the manner in which the pools are assembled complicates the calculation of the joint performance distribution (the pool level loss distribution). Underwriting criteria and screens, and pool composition rules affecting size and diversity are intended to make the pool loss distribution both safer and more predictable through reduced exposure to high-likelihood-of- default units. Similarly, originator/pooler behavior will affect the pool's loss experience. Finally, the economic consequence of the losses depends on the procedures for recognition of losses and recoveries, effective guarantee coverage rates, and potentially on the design of the securities through the timing of the loss guarantee payments.

The pool-level loss distribution -- resulting from the assembly of individual loan loss exposure units -- can also be described according to the severity, frequency, and timing. The pool-level loss distribution can thus be viewed as a loss exposure unit and the firm-level performance measures (across sets of pools) viewed as the aggregation of these loss-exposure units. Analyzing aggregate loss from sets of loans, will be more tractable if the loss exposure units tend to behave as though they are from more stable distributions. However, modeling the firm as a collection of pools is not the direct focus of the model even though it could indirectly address this issue as well.

As the exposure units (either loan level or pool level) are combined to generate an aggregate loss distribution, other considerations are important in determining the particular loss experience manifested. As mentioned above, the risks arising from the sum of a set of individual losses depend on the frequency, severity and timing of the individual units, and on the correlation of the losses across units. Under ideal insurance conditions, the loss exposure units combine to make the aggregate loss distribution more predictable and stable. In the current context, several other forces may impact the aggregate loss distribution as well.

Underwriting criteria attempt to limit exposure to losses by limiting the types of individual exposure units that are aggregated. The idea is to set minimum qualifications at levels that tend to stratify loans into subpopulations with differing probabilities of default, and to pool from loans with lower risks. For this effect to occur, the underwriting standards must be related individually and collectively to the incidence of loss. If loan losses were randomly distributed throughout the loan population, there would be no effect of establishing loan underwriting criteria for qualification. At the other extreme, if all losses occurred within loans that had a particular characteristic, then excluding those loans from the pool would remove all losses from the pool as well. In practice, some, but not all of the loss exposure can be controlled through qualification criteria based on underwriting standards.

Diversification criteria are employed to assemble dissimilar risks to result in a stable sum of risks to "canceling out" or even the loss experiences from dissimilar units. In the extreme, combining two perfectively negatively correlated variables yields a perfectly predictable outcome. Combining two perfectly positively correlated variables together results in a predictable, but more extreme, experience than from either alone. The more typical case is somewhere in between with some degree of risk reduction resulting from the combination of somewhat dissimilar risks.

In addition to combining dissimilar loss exposure units, simply combining more numerous units results also tends to result in more predictability in the aggregate loss measures. However, the qualification criteria can actually result in an increase in the correlation of losses among individual loans than had the loans been randomly assembled, because of the homogenizing effect of the eligibility screens. Because of this effect, the establishment of underwriting standards should implicitly consider the balance between the benefits of diversification across loan features that can be controlled, and the effects of making the underwriting standards more strict and losing both volume and some of the benefits of diversification across dissimilar individual loans.

In addition to the characteristics that result from underwriting criteria, pool composition requirements, and diversification effects (mandated and incidental), originator behavior and pooler behavior can affect the nature and magnitude of the risks embodied in the guarantee. Those that view the guarantee most favorably will be most likely to use it. Thus, it is unlikely that a uniform sample of the qualified subpopulation would be offered for pooling. Instead, the loans offered for pooling are likely to draw more heavily from those nearer the boundary of the underwriting region. The inability to fully identify the risks in the individual loans that meet the underwriting minima leads to the possibility of adverse selection -- those for whom the guarantee is most valuable (most risky loans) will be more likely to self-select from the total population.

Moral hazard is a second behavioral effect. Insurance coverage can lead the insured to act in a more risky manner or to be less likely to mitigate damages. Moral hazard includes both cases where the individual is acting to maximize the value of the insurance, or simple reacts rationally to the lowered costs of experiencing an insured loss. Subordinated positions (deductibles) are used to mitigate the losses passed through to the insurer by more nearly aligning the incentives of the insured with the insurer. In the current context, a subordinated fraction of the loan pool both lessens the remaining insured loss exposure, and improves the incentives for the holder of the subordinated portion to monitor and control risks more closely, and to pursue the least costs methods of work-out, should that need arise.

Limits of insurability arise because of the difficulties in controlling the above risks, although the cost of insuring these pooled risks is lower than the sum of the costs of individually insuring each risk. Thus, the pool can not be made totally riskless without pricing at the point that no individual benefits remain, or establishing criteria which effectively eliminate all potential exposure units from the eligible set. Economic benefits to pooling may still occur with some pool-level loss exposure, but with lower costs than would be the case from the sum of individual insurance costs. This relationship is the most basic justification for pooled, or group insurance.

Actuarial Calculation and Risk-Tolerance Levels

The model employed provides actuarial equivalents at various points of the pool-level loss distributions, while reflecting the consequences of the items discussed above. The primary result is summarized in the mapping of possible loss levels and their associated probabilities to the "cost" of those losses in the form of an annual basis point charge against a declining unpaid principal balance.

To illustrate, for an insurance fund to be solvent 100% of the time, it must contain an amount equal to the largest possible loss of the insured event. To be adequate, say, 90% of the time, the fund would need to contain an amount equal to the loss at the 90th percentile (that point at which 90% of the losses are less than or equal) of the loss distribution and so on for all the points from 0 to 100%. The complete mapping of the loss levels and their associated probabilities, along with the costs of funding the contingent payouts is the actuarial schedule.

The "actuarially fair" point generally refers to the costs required to insure against the mean or the mean plus the smallest insurable increment. It is considered "fair" in that an insurer would just break even between premium income and loss payments by charging exactly the "fair" rate across a large number of pools. Of course, additional expenses of running the insurance firm and the instability of claims through time result in the need to load the insurance premium above the fair or break-even rate to remain solvent through time.[3]

Risk tolerance refers to the funded level of the loss distribution -- and perhaps more directly, to the remaining likelihood for losses that would exhaust the insurance fund. Thus, if the fund displayed a tolerance for exhaustion of 5 times in 100 cases, the tolerance for insolvency is the 5% of the time the insurance fund is inadequate. The implication is that the insurance fee charged would be the rate that generated income in an amount at which 95% of the losses are less than or equal -- the 95th percentile of the loss distribution. It can be shown that multiple pools permit a pooler to accept lower probabilities of adequacy within each pool,

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[3]These definitions are most consistent with the bulk of the literature. In contrast, Towe defines "fair" in its normative form to mean that the premiums are paid by those who benefit and that "funded" is equivalent to the current definition of actuarially fair.

but to retain across-pool solvency if the guarantee fund is fungible across sources of loss. The relevant loss distribution is the joint loss distribution across pools even though the insurance charges may be applied at the pool level.

Insurance analysts also consider the incomplete expectations of the losses (gains) in the regions of solvency and insolvency as defined by the fund's expected balances. Suppose that an insurance fund were established to cover losses distributed uniformly on the interval from 0 to 100 units. Further, the tolerance for insolvency risk is 10% risk of ruin implying the need for 90 units in the reserve fund. The value of the insurance fund depends on the resolution of the insured risk and the implied distribution of firm value after the insurance contingency is resolved. Suppose that in cases of insolvency, the firm is worth 0 -- an event that happens 10% of the time. Under solvent outcomes, the firm is worth the difference between the insurance premium charged (90) and the loss experienced (uniformly distributed over the interval (0,90) containing 90% of the probability). Given uniform losses, the conditional value of losses under solvency of the fund, also termed the incomplete expectation, is 45. Thus the firm value, on average, under conditions of solvency is also 45. Weighting the outcomes by their probabilities, the firm is worth (0*.1)+(45*.9) = 40.50 units. The incomplete expectation of net losses under insolvent outcomes is 5 and the sum of the incomplete expectations is equivalent to the unconditional mean of the loss distribution.

Suppose instead that the loss exposure was distributed uniformly on the interval (81,91). The point corresponding to the 90th percentile of the loss distribution is still 90, but the incomplete expectations of the losses are now 85.5 and .5 for the regions of solvency and insolvency, respectively. The firm now has a naive expected value of 4.5 * .9, or 4.05 units. Thus, the location of the distribution of losses matters both to fund value at a particular level of likelihood for exhaustion, and to the remaining fund value after resolving the risk. Both are important features of the risk tolerance dimension of the guarantee fee evaluation. If there is a profit maximizing motivation, both the incomplete expectation of gains and the willingness to pay by the insured enter into the decision to supply insurance. However, the "maximum difference" between the income and outflows associated with pools is not likely to occur at the lowest risk position, and it also depends on the volume available for pooling for alternate underwriting standards. The pool model, nonetheless, provides an important component for evaluating this issue.

Timing and Loading

In this study, the guarantee fee income stream is analogous to the insurance or reserve fund for comparison to pool losses in the actuarial schedule.[4] Commonly, guarantee fees are administered as a constant-rate basis point charge against unpaid principal balance (UPB). In addition, insurers frequently retain the flexibility to alter guarantee fees in conjunction with a front load, or subordinated position. Thus, in addition to the actuarial schedule, a comparison of the timing of both losses and guarantee income is relevant in describing the desirability of a particular pool's loss/income combination. Because the basis point charge results in premiums that are paid through time, cash flow shortages could occur even in pools in which the lifetime loss and income experiences result in solvency over the entire pool life. Recognizing that financing of future guarantee income for payment of present losses would not be costless, the model retains probabilistic information regarding the timing of losses and the cumulative insurance fund balances through time for any combination of front-load rates, subordinated positions, and basis point charges against UPB.

The annual guarantee fee results in a declining stream of income through time as remaining principal balances decline over time (the remaining loss exposure). Empirically, however, loan losses tend not to occur as a constant fraction of principal balance through time. Rather, losses are low near loan inception, peak at some intermediate point, and decline as the run-offs of both losses and loan balances occur. The divergence in the patterns between fee income and loan losses presents a possibility of cash-flow shortages that, in terms of insolvency risk, modifies the actuarial table to include additional time dimensions. To provide as much information as possible, the model retains the empirical distribution of losses through time, and can provide information about losses through time as well as at points in time.

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[4]FAMC accounting procedures will result in its translation through provisions to an allowance account. The conceptual equivalence between the fee income and the allowance account balance may be substantially affected in practice by accounting requirements.

Data Issues and Description

As documented in *Stress Study of Agricultural Loans,* prepared for the Office of Secondary Market Oversight at FCA (Barry et. al), loan level origination and matched servicing data for agricultural mortgages over a long sample period are exceedingly rare. In that report, potential sources from ERS/USDA, farm record keeping services, commercial banks, life insurance companies, and Farm Credit Banks, were examined as sources of information about origination characteristics, and loan level servicing and charge-off records. The data from Farm Credit Banks of Texas and St. Paul were considered to be the most complete set of data available to evaluate credit risks in agricultural mortgage pools. Since the writing of that report, no new sources of data have been located that challenge the use of those data as most appropriate for the development of the pool-level simulation model, although the composition and dating of the data source is perhaps the most serious limitation in the study.

In principle, all borrower, lender, economic, and competitive characteristics that have any influence on the performance of a loan, are relevant to the simulation model. However, only those characteristics that are useful in underwriting or ongoing monitoring and evaluation likely are available and reasonable to collect from any source. Of particular importance are the origination data from balance sheets, recent income statements, and information related to loan purposes, collateral, and location. For this study, typical underwriting variables that conincide with those included in Farmer Mac's original underwriting requirements were used along with numerous additional loan level variables that permitted additional classifications of performance by variables beyond those used directly in eligibility screens.

The most restrictive requirement for the model is that one of the following sets of data must be available for every loan: (i) lifetime loss information including default/nondefault information as well as timing and charge off amounts for the default cases; (ii) a complete probabilistic description (severity, frequency, timing) of the incidence of loan loss conditional on loan characteristics; or (iii) a partial servicing record and sufficient data to compute the likelihood, severity distribution, and timing distribution for the remainder of the loan life. These requirements insure that the essential information is available that is refined and processed in the simulation model into loss distributions, and upon which the other input variables act to influence the ultimate risks in the pool. The other data fields are used to select eligible seed data and to analyze the sensitivity of the results to changes in conditions, guarantee fee terms, or behavior.

In summary, the important information to retain includes all items affecting losses or loan pooling decisions (for data screens and sensitivity), and some means for observing or generating the loss experience and its required components through time for each loan. On this latter point, the model was developed to accommodate potential future sources of data and in fact is indifferent to whether the actual losses are observed (historical data only), or whether the properties of the loan cause it to be associated with particular probabilistic description of the loss experience that is used to construct a simulated loss experience (live loans could thereby be used). The tradeoffs are that the historic data may be less related to current conditions than are live loans, but the mapping of the characteristics of live loans to their loss-probability measures suffers from the inexactness of all credit assessment models.

Model Description

Figure 1 presents a schematic flowchart of the model.[5] As represented in the model, the user must supply several inputs to control selection of data, pool construction, modification of data-dependent loss experiences, and various other flow and control items. The program then iterates through the process of building pools and constructing the loss experiences. After iterating the number of times specified by the user, the program processes the pool level data and reports an actuarial table, related graphs, and provides information about the probabilities of default across pools.

The user inputs required to run the program are categorized as follows: (i) choice of time-path (distribution) for incidences of default; (ii) items that control the actual simulation and discount rates, (iii) choices that govern the source and timing of the seed data, (iv) modifications to eligibility criteria and sampling regions of eligible subpopulations, (v) pool

[5]The model was written in Gauss-VMI (3.2.14) language for use on a Dos/Windows platform.

characteristics and guarantee features, and (vi) loss modifiers. More complete descriptions of each follow:

(i) The time-path distribution is used to assign probabilities of default to each time period in the simulation for each loan. The time patterns shown in figure 2 are based on a beta distribution with the domain scaled to the number of years that loans can be alive in the pool. Currently, the model incorporates five patterns, but the choice set can be modified to reflect other experiences or time patterns. The choices currently include a distribution fitted to all loans in the Texas data set, a distribution fitted to Farmer Mac Eligible loans only, uniform, accelerated, and delayed patterns. This distribution choice only affects the timing patterns and is otherwise unrelated to the size and frequency of losses.

(ii) Items that control the simulation include the number of iterations, data file pointers and output directions, and various intermediate choices to control the flow of the program depending on the answers to data setup as well as output direction responses.

(iii) Seed data can be drawn from historic data for either the Farm Credit Bank of Texas, or the Farm Credit Bank of St. Paul, or both. The program is currently written in a generic form to accommodate future modifications, substitutions, or extensions to the seed data sources.

(iv) The underwriting requirements to select eligible loans from the data set can default to the set originally employed by Farmer Mac, or can be set independently to establish other eligibility criteria based on the current ratio, debt to asset ratio, loan to value ratio, and debt service coverage ratio. As data limitations permit, other underwriting criteria can be added to this section. The eligibility criteria establish a subpopulation of eligible loans from which the simulation can draw. However, because actual pools may contain loans nearer to the underwriting boundaries, the program also permits the user to restrict further the set of eligible loans that are pooled. A set of "data reigns" that mirror the eligibility criteria, but exclude loans with more favorable ratios can also be invoked. These provisions permit the user to reflect alternative pooling practices, or to generate seed data that closely correspond to actual loan data.

(v) The model also accommodates differences in the pool's target size, amortization details, loan size restrictions if needed, loan seasoning at pool inception, front load fees, and any effective subordination rate. Sensitivity to input items that affect sampling patterns or time patterns can be conducted by rerunning the simulation with changes in only one variable at a time. By contrast, those items that affect only the calculation of guarantee rates and probabilities of adequacy (e.g., front load rates and effective subordination) are changeable within a single simulation via choices to loop back and recompute the guarantee rate information.

(vi) The estimates of loan loss frequency and severity can be modified to permit the calibration of the seed data to other data or other economic environments. These modifications are also useful in analyzing the sensitivity of the model results to changes in loan quality, loss severity and loan type. For example, in row crops, the losses may occur relatively frequently with default costs that may be small fractions of principal, but for nursery stock, the losses may occur only rarely (low frequency) under catastrophic conditions but with near total losses of principal (high severity). The ability to alter frequency and severity independently is important in that it permits a broad set of possible input sets to be represented with a single set of seed data.

Results

Simulation results from various scenarios are discussed below to demonstrate the application of the model and to highlight impacts of modifying particularly important inputs. Only a few of the possible combinations of input variables are presented. However, the framework within which the results are provided can also be utilized to understand future simulations that consider other scenarios, data sources, and changes in input variables. Of primary interest are three kinds of information for each scenario examined: (i) loan losses through time, (ii) probability of guarantee fee adequacy in combination with a front load and/or subordinated position, and (iii) cash flow summaries to assess intertemporal solvency likelihoods.

Each simulation reported herein was conducted with the following: a target pool size of $100 million; a discount rate of 8%; effective pool life and effective amortization life each equal to 14 years; and with the timepath of losses corresponding to that estimated from all eligible loans, except in the case of the accelerated loss scenario. Other inputs and conditions varied across scenarios and are reported in the tables in conjunction with each case. The results from the simulations are reported in two coordinated tables. In the first table, simulation descriptions are provided along with tabulations of input variables, summary loss rates, and summary statistics from the guarantee fee distributions. The second table provides a more complete probabilistic depiction of the loss rate distribution by tabulating elements from the actuarial schedule.

Referring first to Table 1, the base case scenario is provided across the top row. It uses all Texas data from 1979-92 with a total of 25,919 available loans from which 13,611 were eligible based on the base case underwriting standards[6]. There were no frontloading of fees (FLR = 0), and no effective subordination or holdbacks (ESR = 0). The frequency and severity multipliers were set equal to 1 thereby resulting in no changes to the loan-level loss distributions from the data. In the resulting pool, the median loss rate across such pools is .0027, with a mean of .0031 and a standard deviation of .0022. The fact that the mean is greater than the median indicates that the loss distribution is skewed right, as expected, given the effective truncation of losses at zero. As the two measures of central tendency become more divergent, the implication is that more low likelihood, but extreme magnitude events can be found across pools. Changing some of the extreme loss outcomes to even more extreme levels has no effect on the median but can significantly affect the mean. In terms of the guarantee fee distribution that corresponds to the loss levels across pools, the median charge needed to stand against pool losses is 4.7182 basis points per year against the unpaid principal balance with a mean of 5.39 basis points and a standard deviation of 3.7282.

Moving down through rows in the table, various combinations of frontloading (FLR), subordination (ESR), and changes in the frequency and severity are considered relative to the same input data and pool characteristics. Of interest to note, changes in the frontload affect

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[6]The base case set of eligibility requirements includes: current ratio greater than 1.0, debt to asset ratio of no more than .5, debt service coverage ratio of at least 1.25, and a loan to value ratio of .75 or less.

only the needed guarantee fee to stand for the remainder of the losses not covered by up front charges -- there is no effect to the loan-level performance in the pool. By contrast, effective subordination rates (ESRs) higher than 0 remove a portion of the losses experienced from the remaining pool, thereby affecting both the loss rates and the guarantee fee needed to stand for remaining losses. Of the two kinds of buffers against losses, frontloading is more valuable than subordination of the same fraction. This result reflects two effects -- the frontloading occurs sooner than the triggering of an equivalent subordination with resulting time value differences, and there is no refunding of front loaded fees when the fees are greater than resulting pool losses. In the case of subordination, excess levels are of no particular value or cost if not triggered.[7]

Table 2 provides complementary information to better understand the complete location and shape of the loss distribution and corresponding guarantee fee levels. The lefthand panel of table 2 gives the probabilities of adequacy of various basis point charges against unpaid principal balances (UPB). The entries in the table are the cumulative probabilities of losses to the basis point level for that column. For example, the probability that losses are less than or equal to the level covered by a 2 basis point annual guarantee fee is .147 or 14.7%. Equivalently, a 2 b.p. charge is greater than 14.7% of the observed losses across pools. Moving to a 10 b.p. charge increases the likelihood of adequacy to over 90% for the base case in the first row. The right hand panel indicates the needed basis point charge rates at quartile breaks and at probability of adequacy levels of .9, .95, and .98. The latter three percentile levels represent 10%, 5%, and 2% tolerance for insolvency risk, respectively, and reflect levels have been suggested as possible measures of interest.[8] Recall from table 1 that the median loss rate was 4.7182. As shown in table 2, that level corresponds to the 50th

[7]With respect to the model itself, it should be noted that changes in frequency are more demanding of data than changes in severity because the former changes require either exclusion of portions of the data or non-proportional sampling, whereas changes in severity can be applied after a realization of loss is encountered with no impact on sampling procedures.

[8]Quartile breaks, and 90th, 95th, and 98th percentile breaks are commonly reported in insurance studies. It is important to recognize that these guarantee fees are associated with the credit risks of the pools only, and do not reflect any additional expenses of running the pools.

percentile of the loss distribution. At 90% level of adequacy of the loss distribution, an annual guarantee fee of 9.81 basis points is needed.

To integrate the information in the two sides of the table, it can be seen a 10 b.p. rate corresponds to a loss level of just over 90% at .903. If .903 were a column heading in the right hand panel, the entry in the table below it would be 10 basis points. Thus, the left and right hand side panels differ only by whether the basis point charge or likelihood of adequacy is tabulated across prespecified levels of the other. Because changes in the inputs result in widely varying intervals covered by the two distributions, both panels together are needed to fully depict the nature of the relationship between them.

Other scenarios are considered in Tables 1 and 2 to evaluate the influence of more or less stress than represented in the complete available data period under base case underwriting standards. Because 1984-86 is generally agreed to have been a period of historically high stress, a set of scenarios was examined (labeled 2, 3, 5, and 6) that used only data from those three years as seed data. Although the remaining sample sizes are greatly diminished, they still are more than adequate in size to conduct meaningful evaluations. As expected in scenario 2, restricting the sample period in a manner that concentrates the loan level stress among the population from which the pool is constructed also results in significantly higher stress at the pool level. Even so, as indicated in row 1 of that section in table 6.2, a 50 b.p. guarantee fee is still sufficient in over 99% of the cases; alternatively,the 95th percentile of the loss distribution requires approximately 22 b.p. charge to cover the credit risks in the pools. Moving to an accelerated timepath in scenario 3 further exacerbates the loss consequences and adds to the loss carrying costs in intervals where losses exceed guarantee fee receipts. In each scenario, various combinations of front load rates (FLR), effective subordination rates (ESR), frequency of default (Freq.), and severity of default (Sev.) are presented to permit an examination of the effects of changing these features.

Next in Table 1, scenario 4 considers entire sample period, but relaxes the underwriting standards and reigns the qualified loans in nearer to the underwriting limits. Relaxing the underwriting standards resulted in over 9,000 additional loans being qualified, but the pooling reigns restricted just over 15,000 loans for a net reduction in the sample of approximately 6,000 loans. Relative to the original base case, fewer loans remained in the poolable set, and the loss exposure was magnified. This scenario represents non-uniform pooling from eligible loans such that from those qualified, the riskiest subset is pooled first. Interestingly, the median guarantee fee more than doubled, and the probabilities of adequacy at each of the tabulated charge rates dropped significantly. This result indicates the impact of the severe adverse selection in which those for whom the guarantee is most valuable are the first selected from the eligible set for pooling.

As an alternative to the current eligibility screens or to user-specified eligibility criteria at different levels of the same ratios, a credit scoring model was used to define eligibility of loans. The resulting sample was then processed in the pool-level model to evaluate the consequences to the guarantee fees and loss distributions.[9] The credit scoring procedure results in a range of scores that is clearly rejected, a range of scores that is to be further evaluated, and a range of scores that is clearly acceptable. Two specific cutoff scores of interest were processed -- one at the lower end of the range of scores that are to be further evaluated, and one near the upper boundary of the range of scores to be evaluated. In each case, Texas data from 1984-1986 were used to provide a reasonable conservative evaluation and to permit fairly direct comparisons to other scenarios that were evaluated with existing underwriting screens.

In the first case examined (labeled scenario 5), only loans that had scores greater than or equal to 750 were included. By comparison, the potential volume under the credit scored eligibility is similar to that available under the original underwriting standards. Thus, the results are most directly comparable to the second scenario reported in tables 1 and 2. For convenience in making comparisons to guarantee rates and adequacy probabilities, each of the configurations of *FLR*, *ESR*, *Freq.*, and *Sev.* that were reported in scenario 2 are included in scenario 5 as well.

Using the credit scoring model with the 750 point cutoff to select loans results in slightly lower mean and median loss rates. The corresponding b.p. charge rates are likewise

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[9]The credit scoring model was developed using simulated case farms by Ellinger, Barry, and Sherrick at the University of Illinois.

lower suggesting that the credit scoring approach provides greater ability to discriminate among categories of loan performance. Table 2 provides more complete information about the resulting loss distributions under scored eligibility. Again, compared to scenario 2, it can be seen in the right-hand panel that at actuarially equivalent levels, the guarantee fees needed range from approximately 1 to nearly 3 basis points less based on historic loss exposure, and up to 5 basis points lower under the more highly stressed case. Correspondingly, the probabilities of adequacy at any given basis point charge rate is also improved under the scored cases relative to the original eligibility criteria.

Lowering the credit scoring eligibility cutoff to 550 points (scenario 6) results in roughly 50% more loans than at a cutoff of 750. As expected, the loss rates reported in table 1 increase with magnitude changes at the median of .0034 between the two credit scored scenarios. The median and mean basis point guarantee fees increased by 5.8 and 6.8 basis point respectively. And the variability in loss rates increased substantially as well. Turning to Table 2, the increases in the actuarially equivalent guarantee fees that accompany the relaxed standards can be identified. For example, at the 50th percentile (median), the actuarial guarantee fee increases from 11.5 to 17.3 basis points. At lower levels of risk tolerance (higher percentile levels), the difference increases up to approximately 14 basis points at a 98% probability of solvency level.

As in the previous cases, moving through the rows in each scenario indicates the relative magnitudes and effects of various changes. For example, including a 20 basis point front load results in approximately 3 basis point reduction in guarantee fees. Or, including a 1% ESR moves the equivalent exposure (similar rates) from the 75th to the 98th percentile of the loss distribution and significantly improves the probability of adequacy at any given guarantee fee charge. Other tradeoffs in terms of the guarantee can be similarly evaluated.

Summary and Conclusions

The model provides considerable flexibility to consider the impacts on loss rates and associated guarantee fee levels over a wide array of model conditions, pool composition, underwriting, and seed data combinations. Taken in combination, these inputs permit the user to proxy a wide variety of loan types, origination situations, and economic environments. For the majority of cases examined, the current 50 basis point guarantee fee charge is sufficient to cover a large portion of the loss distribution. Tolerance for insolvency risk, intertemporal carrying charges on losses, and additional expenses in running pools are among the other components to consider in judging overall adequacy of guarantee fee strategies from these results. Likewise, as different combinations of front-loading, subordination, and negotiated rates are used, the tradeoffs among these features as illustrated in the model, become increasingly important to understand.

This approach is limited by the availability of data that contain broadly distributed underwriting conditions and loan level performance information through time. The seed data are somewhat dated at this point and may not be broadly representative of current conditions in agriculture. Further, the collection of data, and necessary approximations to employ those data in simulation methods may further diminish the representativeness of the results. The model is coded so that additional selection criteria including scoring approaches, or different eligibility criteria, can be based on whatever data fields are available in the future. The segments of the pooling algorithm that sample from the data are easily separable from the sections that control the initial creation of the data set. As a demonstration, a credit scoring model developed elsewhere was applied to the Texas data set to determine eligibility in two particular cases. Even using data that are becoming dated and have significant differences in type and condition from loans that are expected to be scored in the future, the model demonstrates the advantages at the pool level in the use of credit scoring approaches to determine eligibility. Furthermore, the scoring provides a more consistent and more finely gradated method to evaluate the tradeoffs among attributes and their collective effects at the pool level.

In addition to data concerns, the security design employed during securitization could have significant effects on the consequences of credit losses to the pooler. These potential effects are not considered in this study. And, important behavioral impacts, both by sellers of loans and by guarantors that affect resulting loss exposure were not considered in the model. With these limitations in mind, the model nonetheless serves as a useful tool for evaluating the adequacy of alternative guarantee fee structures, and in assessing the directional effects and relative magnitudes of possible changes in input variables.

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Table 1. Simulation Results - Loss Rates and Gurarantee Fee Summaries

Scenario	FLR	ESR	Freq.	Sev.	Loss rates in Pool: Median	Mean	Std	Basis Points: Median	Mean	Std.
1. Texas Data	0	0	1	1	0.0027	0.0031	0.0022	4.7182	5.3900	3.7277
Years: 1979-92	0.001	0	1	1	0.0027	0.0031	0.0022	2.9966	3.7529	3.6312
Loans: 25919	0.002	0	1	1	0.0027	0.0031	0.0022	1.2749	2.4135	3.3074
Eligible: 13611	0	0.001	1	1	0.0019	0.0024	0.0021	3.3374	4.0815	3.6503
	0	0.01	1	1	0.0000	0.0001	0.0005	0.0000	0.1923	0.8923
	0	0	1	2	0.0055	0.0063	0.0043	9.4364	10.7800	7.4554
	0	0.01	1	2	0.0000	0.0012	0.0028	0.0000	1.9927	4.8465
	0	0	1	0.5	0.0014	0.0016	0.0011	2.3591	2.6950	1.8639
	0	0	2	1	0.0043	0.0049	0.0029	7.3410	8.4799	5.0262
	0.001	0	2	1	0.0043	0.0049	0.0029	5.6193	6.7644	5.0175
	0.002	0	2	1	0.0043	0.0049	0.0029	3.8977	5.1334	4.9130
	0	0	2	2	0.0085	0.0099	0.0058	14.6819	16.9597	10.0525
2. Texas Data	0	0	1	1	0.0075	0.0078	0.0032	12.9766	13.4415	5.4423
Years: 1984-86	0.001	0	1	1	0.0075	0.0078	0.0032	11.2550	11.7212	5.4392
Loans: 5586	0.002	0	1	1	0.0075	0.0078	0.0032	9.5333	10.0074	5.4237
Eligible: 2624	0	0	1	2	0.0151	0.0156	0.0063	25.9533	26.8830	10.8846
	0	0.01	1	2	0.0074	0.0080	0.0059	12.6838	13.7506	10.1905
	0	0	1	0.5	0.0038	0.0039	0.0016	6.4883	6.7207	2.7212
3. Texas Data	0	0	1	1	0.0088	0.0090	0.0035	15.0857	15.5782	6.0911
Years: 1984-86	0.001	0	1	1	0.0088	0.0090	0.0035	13.3640	13.8566	6.0911
Loans: 5586	0.002	0	1	1	0.0088	0.0090	0.0035	11.6424	12.1388	6.0831
Eligible: 2624 Timepath:	0	0.01	1	1	0.0005	0.0016	0.0023	0.7858	2.8104	3.9967
Accelerated	0	0	1	2	0.0175	0.0181	0.0071	30.1714	31.1565	12.1821
4. Texas Data Years: 1979-92	0	0	1	1	0.0059	0.0066	0.0036	10.1809	11.3731	6.1724
Loans: 25919	0.001	0	1	1	0.0059	0.0066	0.0036	8.4593	9.6529	6.1699
Eligible: 7550	0.002	0	1	1	0.0059	0.0066	0.0036	6.7376	7.9557	6.1360
.9<CR<100 .2<DA<.6	0	0.01	1	1	0.0000	0.0010	0.0022	0.0000	1.7757	3.7837
.3<LTV<.9	0	0	1	2	0.0118	0.0132	0.0072	20.3618	22.7462	12.3448
1<DSCR<4	0.002	0	1	2	0.0118	0.0132	0.0072	16.9185	19.3059	12.3398
5. Texas Data	0	0	1	1	0.0067	0.0068	0.0027	11.5078	11.7358	4.6400
Years: 1984-86	0.001	0	1	1	0.0067	0.0068	0.0027	9.7862	10.0145	4.6441
Loans: 5580 Eligible: 2576	0.002	0	1	1	0.0067	0.0068	0.0027	8.0645	8.3049	4.6209
Scored>750	0	0.01	1	1	0.0000	0.0008	0.0015	0.0000	1.3280	2.5007
(84_86cs750)	0	0	1	2	0.0134	0.0136	0.0054	23.0157	23.4717	9.2894
	0	0.01	1	2	0.0056	0.0061	0.0049	9.6123	10.5781	8.3839
	0	0	1	0.5	0.0033	0.0034	0.0013	5.7539	5.8679	2.3224
6. Texas Data	0	0	1	1	0.0101	0.0108	0.0045	17.3295	18.5184	7.7154
Years: 1984-86	0.001	0	1	1	0.0101	0.0108	0.0045	15.6078	16.7968	7.7153
Loans: 5580 Eligible: 3852	0.002	0	1	1	0.0101	0.0108	0.0045	13.8862	15.0763	7.7129
Scored>550	0	0.01	1	1	0.0027	0.0036	0.0037	4.5860	6.2690	6.4329
(84_86cs550)	0	0	1	2	0.0201	0.0215	0.0090	34.6589	37.0369	15.4306

Table 2. Simulation Results - Loss Distribution and Guarantee Fee Schedules

					Probability of Adequacy at Basis point Charge Rates									Basis Point Rates at Percentile Levels					
Scenario	FLR	ESR	Freq.	Sev.	2	10	20	30	40	**50**	60	70	80	0.25	0.5	0.75	0.9	0.95	0.98
1. Texas Data	0	0	1	1	0.147	0.903	0.997	1.000	1.000	1.000	1.000	1.000	1.000	2.8343	4.7182	6.8282	9.8100	13.7762	16.3935
Years: 1979-92	0.001	0	1	1	0.377	0.931	0.999	1.000	1.000	1.000	1.000	1.000	1.000	1.1127	2.9966	5.1066	8.0883	12.0545	14.6719
Loans: 25919	0.002	0	1	1	0.591	0.949	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.0000	1.2749	3.3849	6.3667	10.3329	12.9502
Eligible: 13611	0	0.001	1	1	0.323	0.925	0.999	1.000	1.000	1.000	1.000	1.000	1.000	1.4967	3.3374	5.4276	8.4207	12.5773	15.0583
	0	0.01	1	1	0.959	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.0000	0.0000	0.0000	0.0000	1.3726	3.5408
	0	0	1	2	0.058	0.538	0.903	0.964	0.997	1.000	1.000	1.000	1.000	5.6687	9.4364	13.6564	19.6200	27.5524	32.7870
	0	0.01	1	2	0.800	0.925	0.984	0.999	1.000	1.000	1.000	1.000	1.000	0.0000	0.0000	1.1034	6.4050	14.6973	19.6202
	0	0	1	0.5	0.415	0.997	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.4172	2.3591	3.4141	4.9050	6.8881	8.1968
	0	0	2	1	0.024	0.715	0.965	0.997	1.000	1.000	1.000	1.000	1.000	5.0198	7.3410	10.7257	14.7384	18.8565	22.8609
	0.001	0	2	1	0.124	0.795	0.972	0.998	1.000	1.000	1.000	1.000	1.000	3.2982	5.6193	9.0040	13.0167	17.1348	21.1392
	0.002	0	2	1	0.297	0.865	0.981	0.998	1.000	1.000	1.000	1.000	1.000	1.5765	3.8977	7.2824	11.2951	15.4132	19.4176
	0	0	2	2	0.001	0.243	0.715	0.905	0.965	0.990	0.997	1.000	1.000	10.0396	14.6819	21.4514	29.4768	37.7129	45.7218
2. Texas Data	0	0	1	1	0.003	0.288	0.895	0.992	0.999	0.999	0.999	1.000	1.000	9.4354	12.9766	16.8308	20.1675	22.4688	24.8648
Years: 1984-86	0.001	0	1	1	0.007	0.407	0.936	0.996	0.999	0.999	1.000	1.000	1.000	7.7138	11.2550	15.1092	18.4459	20.7472	23.1432
Loans: 5586	0.002	0	1	1	0.047	0.534	0.966	0.996	0.999	0.999	1.000	1.000	1.000	5.9921	9.5333	13.3875	16.7242	19.0255	21.4215
Eligible: 2624	0	0	1	2	0.001	0.033	0.288	0.652	0.895	0.980	0.992	0.997	0.999	18.8709	25.9533	33.6616	40.3350	44.9376	49.7297
	0	0.01	1	2	0.111	0.394	0.747	0.938	0.988	0.996	0.999	0.999	0.999	5.7840	12.6838	20.1000	26.4278	30.9157	36.3116
	0	0	1	0.5	0.008	0.895	0.999	1.000	1.000	1.000	1.000	1.000	1.000	4.7177	6.4883	8.4154	10.0838	11.2344	12.4324
3. Texas Data	0	0	1	1	0.001	0.193	0.777	0.982	1.000	1.000	1.000	1.000	1.000	11.1978	15.0857	19.2241	24.0300	26.3251	29.6208
Years: 1984-86	0.001	0	1	1	0.007	0.294	0.842	0.987	1.000	1.000	1.000	1.000	1.000	9.4762	13.3640	17.5025	22.3084	24.6034	27.8991
Loans: 5586	0.002	0	1	1	0.026	0.402	0.881	0.996	1.000	1.000	1.000	1.000	1.000	7.7545	11.6424	15.7808	20.5867	22.8818	26.1775
Eligible: 2624	0	0.01	1	1	0.597	0.925	0.999	1.000	1.000	1.000	1.000	1.000	1.000	0.0000	0.7858	4.4084	8.8763	11.2494	14.2520
Timepath: Accelerated	0	0	1	2	0.000	0.020	0.193	0.491	0.777	0.925	0.982	0.998	1.000	22.3957	30.1714	38.4482	48.0600	52.6501	59.2415

Table 2. (continued) Simulation Results - Loss Distribution and Guarantee Fee Schedules

Scenario	FLR	ESR	Freq.	Sev.	Probability of Adequacy at Basis point Charge Rates 2	10	20	30	40	**50**	60	70	80	Basis Point Rates at Percentile Levels 0.25	0.5	0.75	0.9	0.95	0.98
4. Texas Data	0	0	1	1	0.006	0.481	0.910	0.988	0.997	1.000	1.000	1.000	1.000	6.7558	10.1809	14.5336	19.4702	22.9020	27.5236
Years: 1979-92	0.001	0	1	1	0.041	0.592	0.939	0.991	0.999	1.000	1.000	1.000	1.000	5.0342	8.4593	12.8119	17.7485	21.1804	25.8019
Loans: 25919 Eligible: 7550	0.002	0	1	1	0.142	0.709	0.956	0.994	1.000	1.000	1.000	1.000	1.000	3.3125	6.7376	11.0903	16.0269	19.4587	24.0803
.9<CR<100	0	0.01	1	1	0.758	0.954	0.993	1.000	1.000	1.000	1.000	1.000	1.000	0.0000	0.0000	1.8161	6.0519	9.8099	13.7569
.2<DA<.6 .3<LTV<.9	0	0	1	2	0.001	0.112	0.481	0.766	0.910	0.968	0.988	0.995	0.997	13.5117	20.3618	29.0672	38.9403	45.8041	55.0471
1<DSCR<	0.002	0	1	2	0.014	0.247	0.592	0.826	0.939	0.977	0.991	0.995	0.999	10.0680	16.9185	25.6239	35.4970	42.3608	51.6038
5. Texas Data	0	0	1	1	0.003	0.383	0.951	0.999	0.999	1.000	1.000	1.000	1.000	8.3992	11.5078	14.6081	17.2402	19.9244	22.4033
Years: 1984-86	0.001	0	1	1	0.025	0.521	0.976	0.999	0.999	1.000	1.000	1.000	1.000	6.6775	9.7862	12.8864	15.7685	18.2027	20.6817
Loans: 5580 Eligible: 2576	0.002	0	1	1	0.069	0.664	0.988	0.999	0.999	1.000	1.000	1.000	1.000	4.9559	8.0645	11.1648	14.0469	16.4811	18.9600
Scored>750	0	0.01	1	1	0.762	0.990	0.999	0.999	1.000	1.000	1.000	1.000	1.000	0.0000	0.0000	1.8452	4.3320	6.5443	8.8690
(84_86cs750)	0	0	1	2	0.000	0.051	0.383	0.778	0.951	0.995	0.999	0.999	0.999	16.7984	23.0157	29.2162	34.9804	39.8488	44.8066
	0	0.01	1	2	0.170	0.522	0.864	0.976	0.997	0.999	0.999	0.999	1.000	3.9515	90.6123	15.6572	21.0150	25.7598	30.6789
	0	0	1	0.5	0.028	0.951	0.999	1.000	1.000	1.000	1.000	1.000	1.000	4.1996	5.7539	7.304	8.7451	9.9622	11.2017
6. Texas Data	0	0	1	1	0.000	0.128	0.634	0.914	0.992	0.999	1.000	1.000	1.000	12.8475	17.3295	23.5125	28.9866	32.1943	36.4071
Years: 1984-86	0.001	0	1	1	0.001	0.193	0.686	0.939	0.993	0.999	1.000	1.000	1.000	11.1258	15.6078	21.7908	27.2649	30.4727	34.6855
Loans: 5580 Eligible: 3852	0.002	0	1	1	0.012	0.283	0.747	0.964	0.996	0.999	1.000	1.000	1.000	9.4042	13.8862	20.0692	25.5433	28.751	32.9638
Scored>550	0	0.01	1	1	0.332	0.743	0.966	0.996	0.999	1.000	1.000	1.000	1.000	0.4192	4.586	10.128	15.2874	18.4491	23.0381
(84_86cs550)	0	0	1	2	0.000	0.009	0.128	0.353	0.634	0.803	0.914	0.970	0.992	25.695	34.6589	47.025	57.9732	64.3887	72.8143

Figure 1. Guarantee Valuation Flowchart