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Conditioning Mortgage Credit Analysis on Climate Risk: General Approach & Florida Case Study

Eknath Belbase & Alex Levin

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Conditioning Mortgage Credit Analysis on Climate Risk: General Approach & Florida Case Study

Eknath Belbase & Alex Levin,
Andrew Davidson & Co., Inc. (AD&Co.)

MORTGAGE BANKERS ASSOCIATION

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Introduction

In recent years, there has been increased interest in measuring exposure to climate risk, both from regulators and investors. At Andrew Davidson & Co., Inc. (AD&Co.), we have also seen interest from market participants engaged in making portfolio and risk decisions who would like to be able to incorporate climate risks into their analyses and decision metrics.

There are two predominant ways to incorporate climate risks — a macro approach and a granular approach. In the next section we discuss the pros and cons of each approach and argue that the granular is preferable. We then describe our granular solution that involves conditioning our existing behavioral and house price models on variability in climate risk as represented economically by variability in rising insurance premiums.

TWO APPROACHES FOR INCORPORATING CLIMATE RISK

We have observed two distinct approaches begin to emerge to incorporate climate risk into portfolio and risk analysis. The first is what we would call the "macro" approach. For example, creating state- or MSA-level stress tests for exposure to wildfire risk or flood risk, and then examining how much of an institution's portfolio is exposed to each.

The advantage of this method is that it is relatively simple to set up and execute and would be a step towards meeting regulatory needs. The limitations of this approach are many: within each state, differences of a few feet in elevation or construction can mean the difference between complete losses on a house or none during a flood. Likewise, there is no way to compare whether it is better to deploy a dollar of risk capital in location A taking more flood risk or in location B taking more exposure to wildfire risk. There is no way to mitigate or limit risk using this method other than avoiding an entire state or MSA. Additionally, pricing and risk-based capital analysis cannot be performed consistently because those are typically loan-level and property-level in their granularity already.

The second approach is what we call the "granular" approach. Granular analysis would require property-level climate risk metrics which are used to condition existing loan-level analytics already used to compute all the required metrics for portfolio and risk decision-making. The disadvantage of this approach is that it is considerably more complex and involved to set up than the macro approach. The advantages of this approach, once set up, include the ability to meet all the requirements from regulators and investors by rolling up granular data but retaining the ability to make loan-level pricing and risk decisions by keeping the data appropriately granular based on the particular climate hazard. As climate models improve, the resolution of this approach will improve as well.

The last observation to make on the two approaches is that if some institutions exclusively take the macro approach and others take the granular approach, we expect the highest risk properties and loans to migrate from the second group to the first group over time. Because the granular approach can satisfy both sets of needs, and we anticipate that many of our clients will want the ability to incorporate climate risks into pricing and risk management, we have chosen this approach.

THE GRANULAR APPROACH

In the remainder of this article, we focus on AD&Co.'s granular analytical approach to measuring how climate risk may impact each of the traditionally measured risk categories: market, interest rate/prepayment, and credit risk. Our goal is to do so in a way that flows through to analytics that institutions rely on: risk-based capital, mortgage insurance premiums, risk-based loan pricing, relative value metrics, portfolio return distributions, etc. Ideally, such a method would also allow attribution of risk exposure to particular sub-types of climate risk.

Core sub-types of climate risk include: coastal and inland flood risk, wildfire risk, cyclonic storm risk (wind, rain, hail), sea-level rise (including subsidence), and water and heat stress. Some of these risks are that of one-time events having higher frequency and severity than in the past; others could be characterized as becoming ongoing nuisances that reduce the utility or enjoyment of a particular area, or increase the ongoing costs required to continue to utilize or enjoy that space. We should point out that due to the nature of reinsurance pricing and its impact on insurance pricing, this conceptual distinction between one-time less

frequent events targeting specific areas may be superficial at an economic level. The incidence of risk can be transmitted as increased ongoing insurance or other costs to a much larger area (where climate models show the overall risk of such events going up) than that impacted by any particular one-time event.

Viewed through this lens, municipal debt, commercial property and debt, and single-family and multifamily property and mortgages are all potentially impacted long-dated asset classes.

We begin by asking some questions:

1. How might individual and commercial insurance premiums (for flood insurance, catastrophe insurance, fire insurance, homeowner, or commercial property insurance) be impacted as a function of different levels of risk exposure?

2. For the highest risk areas, would property tax rates also need to increase in order to increase investment in public infrastructure that mitigates the worst risks or rebuilds damaged infrastructure?

3. How might this combination of increased costs impact future appreciation of both commercial and residential properties?

4. In addition to the observable impact on real estate pricing, might there be additional impacts on the movement of firms and individuals, both in response to priced risks and to perceptions of those risks ahead of any full re-pricing?

Finally, while on the topic of granularity, it is worth noting that different climate risks inhabit somewhat different "zones" of granularity. At the highest level, increased cyclonic storm risks impact multi-state regions and it is difficult to differentiate pure storm risk within these larger regions; similarly, drought/water stress and heat stress also tend to impact geographically larger regions. Next, wildfire risk appears to be increasing in zones of intermediate resolution, and even though individual fires impact fairly concentrated zones, wildfire premium increases are impacting considerably larger zones. At the other end of the spectrum, sea-level rise, coastal, and inland flood risks appear to vary greatly even within MSAs and zip codes, so property-level analysis which takes construction, elevation, and other land feature variation into account is particularly appropriate.

Review of Literature

There is a sizable body of published research on the topic of hazard risks and their subsequent impacts on real estate pricing. We look at some relevant highlights from this literature and note some papers on the related topic of adverse selection. Following the review, we discuss details of our granular approach, which has been inflected by this work.

Bakkensen & Barrage (2017) find direct evidence of belief heterogeneity in flood risks and evidence of self-sorting of homeowners into higher risk areas (e.g., climate skeptics tend to continue to buy in higher risk locations, everyone else moves). The paper also explains why actual flood events have a greater price impact than those predicted by risk models (as perceived via insurance premiums).

Using 460,000 sales between 2007–2016, Bernstein et al. (2019) find the sea level rise (SLR) exposure discount to be 7% and growing over time. It finds that the SLR discount varies, with higher discounts in markets with a higher percentage of sophisticated investors, and lower discounts in primarily owner-occupied markets. The paper also finds no rental market discount.

Blessing et al (2017) find that house price appreciation (HPA) tends to increase after re-building closest to the central area of a fire (due to code updates and more resilient structures being forced to be built by the California code) and that delinquency rates are the lowest for the largest fires (due to more mobilization of state resources and larger insurance payouts), but that these trends are unlikely to be sustainable given the structure of the insurance.

Keenan et al. (2018) utilize Miami-Dade County, Florida (MDC) as a case study to test the hypothesis that the rate of price appreciation of single-family properties in MDC is positively related to and correlated with incremental measures of higher elevation (the 'Elevation Hypothesis'). As a reflection of an increase in observed nuisance flooding and relative SLR, the second hypothesis is that the rates of price appreciation in the lowest elevation cohorts have not kept up with the rates of appreciation of higher elevation cohorts since approximately 2000 (the 'Nuisance Hypothesis'). The findings support a validation of both hypotheses and suggest the potential existence of consumer preferences that are based, in part, on perceptions of flood risk and/or observations of flooding.

One common theme through much of the literature is to tie home price data to risk data, which led directly to our choice of insurance premiums (for homeowners, wildfire, and flood) as the most easily observable and salient variable. The key question when we began this project was how exactly homeowners of different levels of expertise or education might go about assessing the exact level of risk; using insurance premiums provides a uniform, relatively objective and available measure that will impact all homeowners who have mortgages regardless of their degree of belief in climate change or changing risks due to climate change.

Ortega & Taspmar (2018) analyze the effects of Hurricane Sandy on the New York City housing market using all housing sales for 2003–2017. Their estimates show gradual emergence of a price penalty among flood zone properties that were not damaged by Sandy, reaching 8% in 2017 and showing no signs of recovery. In contrast, damaged properties suffered a large immediate drop in value following the storm (17–22%), followed by a partial recovery and convergence toward a similar penalty as non-damaged properties. The partial recovery in the prices of damaged properties likely reflects their gradual restoration. However, the persistent price reduction affecting all flood-zone properties is more consistent with a learning mechanism. We would note that it is also consistent with our belief that

insurance costs are a primary economic driver of affordability and hence price dynamics that diffuse risk information beyond properties impacted by any single event.

Ouazad and Kahn (2019) examine whether lenders' sales of mortgages with loan amounts right below the conforming loan limit increase significantly after a natural disaster that caused more than a billion dollars in damages. Results suggest a substantial increase in securitization activity in years following such a billion-dollar disaster. The increase is larger in neighborhoods for which such a disaster is "new news." This suggests that the government-sponsored enterprises (GSEs) may experience significant adverse selection already and supports our belief that any entity which chooses a macro approach will likely face similar adverse selection.

Elements of the Granular Approach

Our granular approach for incorporating climate risks into mortgage analytics consists of the following steps:

- Forecasting insurance premium increases at the appropriate level of granularity. There are several vendors with deep climate expertise who can provide AD&Co. with these inputs (e.g., ICE, Jupiter Intelligence, 427, and RMS). As we continue to improve our granular approach, future versions may also include additional cost impacts, such as a rise in local property taxes due to the need to rebuild or harden public infrastructure.

- Incorporating these insurance premium increase forecasts to condition our suite of behavioral models, including prepayment models (especially turnover) and default models (collectively, the LoanDynamics Model, or LDM).

- Conditioning of our existing house price appreciation (HPA) simulation and valuation grid to take account of the insurance premium increases over the forecast horizon. This component also flows through to the severity upon default component of our behavioral models.

Given the need for potentially property level data, a necessary first step for climate-conditioned mortgage analytics runs would be to exchange the locations with the climate analytics provider and download location-specific data. This would be followed by calls to the AD&Co. Climate Impact Suite. Attribution to the climate dimension could be calculated as the difference between climate-conditioned LDM and base LDM.[1]

In the next two sections, we focus on the use of cost forecasts to climate condition our behavioral models and HPA models respectively. The appendix contains background information on LDM and our HPA model and how they interact.

1. An overview of our LDM, LoanDynamics Model, is described in appendix.

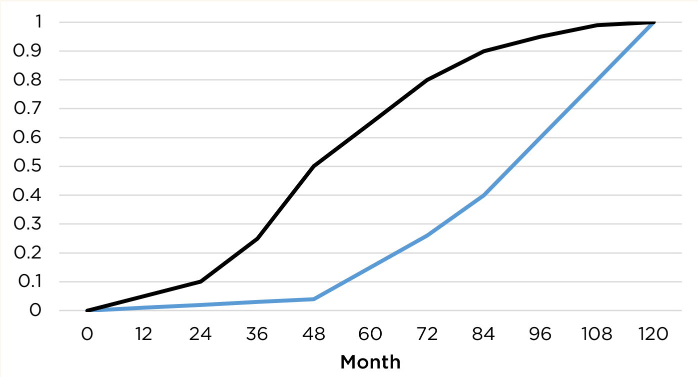
BEHAVIORAL MODELING APPROACH

Climate conditioning our behavioral models includes two components: user-tuning scenarios for the speed at which future losses will be priced into all the components of the mortgage holders' costs (homeowners, flood, wildfire insurance, and property taxes) and conditioning our prepayment and delinquency transitions to vary as a function of these cost increases. Our severity model takes as an input a forward house price path; conditioning house prices for climate will imply that our severity function is also climate conditioned.

The reason for the inclusion of the first component is that climate data providers model losses as a function of different climate scenarios, but the rate at which these rising losses are incorporated into the market price of insurance varies by type of insurance and location. For example, Florida homeowners' insurance rate increases above certain thresholds require elaborate processes involving community comment; policy holders facing large increases also have a state-backed insurer which, for a time, may limit the rate at which observed increases in losses are passed through to observable policy premiums. California wildfire faces a similar dynamic via the FAIR plan, a state-established insurer of last resort collectively backed by the insurance industry. Federal flood insurance has similar "speed bumps" that could delay the recognition of elevated levels of risk in homeowner costs. Such policy-driven factors are less amenable to our modeling approach and scenario analysis around this factor may be preferable.

In Figure 1 we graph some hypothetical user scenarios for potential time periods over which premiums could catch up to actual loss data. The vertical axis represents the current gap between insurance premiums collected and the amount that would be required to be collected to have no underwriting loss. The black line shows a scenario where cost increases (towards a path of actual losses that is itself still rising over time) are allowed relatively quickly, as opposed to the blue line where the process of premium rationalization takes longer. In the second scenario, it is likely that more private insurers would exit the market in question and more of the risk would adversely select into state-backed pools.

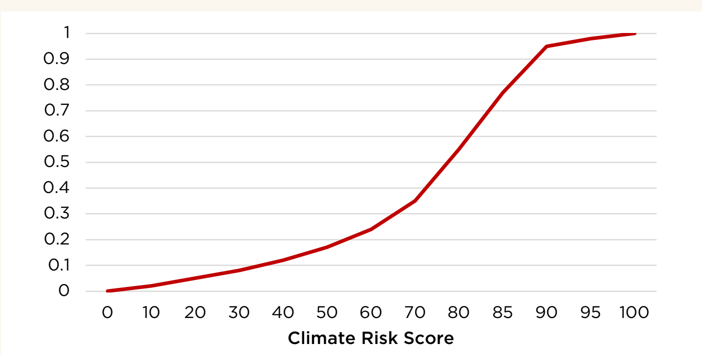
Figure 1: **Scenarios for Insurance Cost Pricing: Insurance Cost (as a % of Repricing)**



The second component links increases in costs to delinquencies and borrower turnover. Our prior would be that in the highest risk areas, as insurance costs rise enough to approach the same order of magnitude as mortgage payments, there would be some increased propensity to move to a lower cost location (assuming the property has a current LTV at the time allowing such a sale, and that the location is still attractive to other borrowers). In the cases where the CLTV or the housing market doesn't allow the sale to occur, the cost impact could also result in an increased delinquency transition.

In Figure 2 we show an idealized curve linking individual climate risk score to the percent of the maximum cost-reset effect on defaults — by this we mean the maximum increase that we would expect in the underlying default rate given the known credit risk factors which are already used by our current default models, but ignoring any impact from affordability issues caused by increased insurance premiums (which are currently not a model factor).

Figure 2: **Default Rates as a Function of Climate Risk Score (% of Maximum Effect)**



In practice, the model would be fed a 30-year forecast of insurance cost increases for each type of insurance (homeowners, flood, wildfire). While data on the impact of increasing climate risks (as reflected in insurance premiums) on turnover and delinquency behavior is currently sparse and limited, we do have a conceptual precedence for measuring the impact of mortgage cost increases on borrower turnover and default behavior from the ARM universe.

Prior to the financial crisis, an increase in interest-only and negative amortization mortgages resulted in significant payment shocks when the interest-only or negative amortization periods ended. The data from this period can be used to form initial expectations for the potential size of any pay shock effect that would occur to what is now a predominantly fixed-rate mortgage universe. In effect, rapid rises in annual insurance premium rates add a yearly floater to the otherwise fixed-rate mortgage payment. When the initial cost of insurance is small in magnitude relative to the fixed-rate mortgage payment, we might expect little to no impact; as the cost of insurance exceeds the size of annual property tax payments (a threshold which has already been crossed in many counties in Florida) and becomes a significant percentage of the monthly mortgage payment, this floater becomes a source of risk in its own right.

Following this line of thought, each homeowner's liabilities consist of the mortgage, the insurance contracts on the home, and the property tax bill. Even if the first is fixed, the latter set are annual floaters that rarely adjust downwards; all floating liabilities might be expected to have some relationship to climate risk, with increases higher than the rate of income growth more likely to have behavioral impact. Over time, this approach to modeling the behavioral impact on turnover and delinquency rates of cost increases will be based on a wide range of data from multiple higher risk locations. For the initial versions of the model, we expect to leverage data from areas where insurance costs have already been rising rapidly, such as coastal Florida, parts of California, and Louisiana.

In the next section, we turn to our house price modeling approach under climate conditioning.

HOUSE PRICE MODELING APPROACH

With regards to home price modeling, there are several factors to consider:

- The effect of increasing property insurance caused by climate change;
- The effect of uninsured or underinsured properties; and
- The effect of population attrition and falling demand of housing in the affected areas.

For the purpose of this paper, we limit our attention to the first two factors, using flood insurance underpricing/underinsurance in the state of Florida.

INPUTS

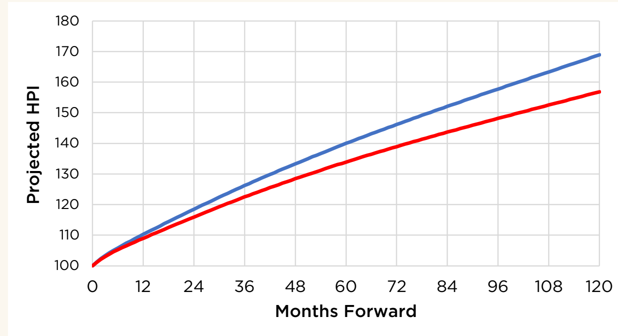
According to Intercontinental Exchange's (ICE) data, the average collected property premium rate for flood insurance is 0.23% — measured relative to replacement value. This level includes all properties, both insured and uninsured. Per ICE's analysis, the objective evaluation of expected annual damages should be around 1.1%; the actual fair premium to be collected is expected to be even higher. For the purpose of our analysis, we assume a 1% flood insurance premium hike measured as additional annual interest on a loan. This will offset various risk-reducing effects (e.g., replacement values being typically lower than loans).

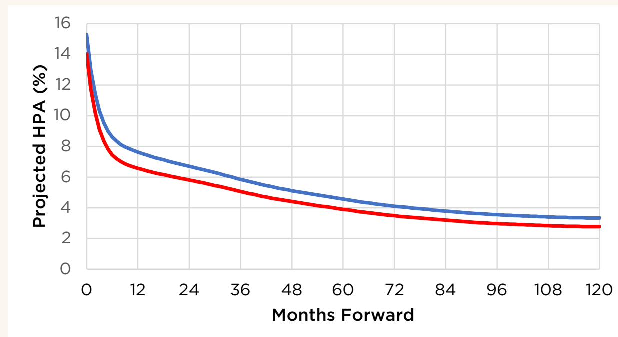
CONVERSION INTO AN HPI OUTLOOK

The economic cost of borrowing is one of the key inputs in AD&Co.'s HPI model. That cost includes mortgage payments, down payment (viewed as another expensive loan), and mortgage insurance (if any). While we didn't explicitly consider the cost of property insurance (or other costs such as real estate taxes and fees), these can be easily added to the model's tuning process.

To illustrate the cost-conversion process, Figure 3 depicts two lines for the Florida home price index (HPI) and the home price appreciation (HPA) rate. The blue lines are from AD&Co.'s HPI3 model. The red lines reflect the downward adjusted outlook coming from the properly increased cost of borrowing (that is equivalent to the increased cost of flood insurance).

Figure 3. Projected HPI and HPA for Florida





ECONOMICS OF LOAN GUARANTEES

Finding a large effect on the base-case economics is not expected, given the positive trend in the housing market. The two projected HPI lines (Figure 3) point to appreciation, even if they differ by 4.5% in 5 years and by 7.7% in 10 years. On the other hand, in a strong downturn, the same relative depression may matter in estimating loan performance.

To solve for the guarantee fee and economic capital, we apply our Capital Charge methodology as described in Davidson and Levin (2014). The method requires two inputs: return on equity (ROE) (taken as 8%) and protection confidence (set to 99%). We then formulate two conditions:

- The expected ROE computed from all cash flow components (premium, losses, release of capital) should be equal to the given target, and
- Given the protection confidence level, the erosion of capital is at or below the worst scenario.

The method is implemented on the AD&Co. standard 20-scenario grid, and available in the LoanKinetics system.[2] The equivalent climate-induced short-term HPA and long-term HPA dials get added to the already existing dials that define the 20 scenarios. Note that the base-cases loss expectation contributes minimally to the guarantee fee, which depends mainly on unexpected losses and is computed concurrently with economic capital.

RESULTS

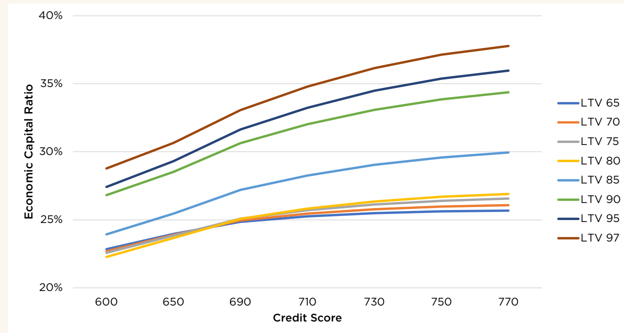
For a range of FICO and original LTV (OLTV) typically utilized for credit analyses of GSE loans, Figure 4 depicts economic capital and annual guarantee fee, both stated relative to the values obtained for the current cost of flood insurance. Note that standard private mortgage insurance (PMI) is assumed for above-80 OLTV loans. The analysis uses market conditions as of 9/30/2022.

The perceived spike in the cost of flood insurance results in a 20% to 35% increase in the cost of GSE guarantees, as well as economic capital. Within this range, the relative increase is somewhat stronger for high-FICO loans and also for high-LTV loans. This dependence on FICO is consistent with the observation that lower-quality borrowers are less sensitive to economic drivers, in general. Given the FICO level, higher-LTV loans tend to be more sensitive to HPA, even if they carry PMI (which provides limited protection).

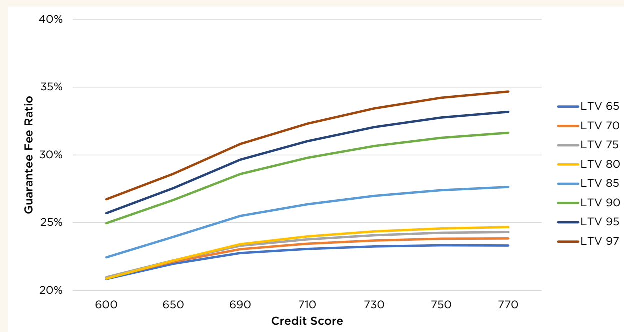
The dependence of these ratios on the chosen levels of ROE and confidence is very modest and does not warrant a separate review.

Figure 4. Guarantee Fee and Capital Increase from the Spike in Flood Insurance Premium

Economic Capital



Guarantee Fee



RELATIVE EFFECT AS A FUNCTION OF MARKET

Our analysis used market conditions as of September 30, 2022. Interest rates had been much lower prior to 2022 and the HPI outlooks had been stronger posing the following question: How is the theoretical effect we attempt to measure affected by market conditions?

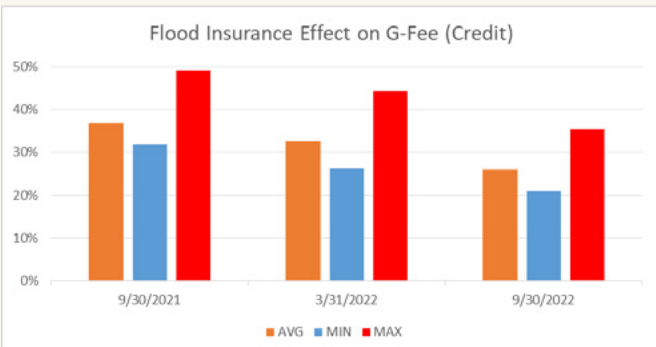
One obvious effect we can identify is the relative decline of the spike in flood insurance cost once it is compared with the increased loan payment. Therefore, we expect that the higher loan rates have recently reduced the effect of climate-related cost increase.

2. Scenario 7 represents a base case whereas scenarios 8 to 19 reflect credit stresses in increasing order. The stresses are achieved by a combination of economic stresses (home prices, interest rates) coupled with adverse model errors.

Another driver is the credit outlook. When it improves, the same spike in cost will mean more, on a relative basis. Figure 5 illustrates these concepts presenting minimal, maximal, and average effects from the OLTV/FICO permutation table, for three points of history.

Figure 5. Effect of Market Conditions

	9/30/21	3/30/22	9/30/22
Primary Rate	3.00%	4.74%	6.79%
1% to Total Cost	13.6%	11.9%	10.3%
HPI Outlook	Very Strong	Positive	Moderate



The role of a 1% increase in flood insurance represented 13.6% of the borrower total cost on 9/30/2021; it fell to 11.9% on 3/31/2022 and to 10.3% on 9/30/2022. The HPI outlook has worsened as well. These market factors would explain the gradual decline in the climate-induced effect over time; it was stronger a year ago. As seen from Figure 5, across the range of FICO, OLTV, and market conditions, the relative increase in g-fee ranges from 20% to 50%.

Conclusions

The incorporation of property-level climate risk forecasts as encapsulated in rising insurance premiums marks a significant step in the evolution of mortgage models, which have gone from generic pool-level models, to loan-level models which have begun to use information of increasing granularity on borrowers and properties.

The forecasting of granular economic drivers, such as increased insurance cost, the ability to distinguish regions with greater and slower property tax cost increases, and, down the road, the ability to identify second order local economic impacts from differences in climate risk are potential future developments. The current article describes work that is a small initial step in this direction.

Among other findings, we assess that the g-fee or the economic capital for loans in Florida would go up 20% to 50% from their present levels — using the diminished, cost-adjusted, HPI outlook alone. This range covers permutations of FICO, OLTV, and starting economic conditions.

Appendix: A Summary of AD&Co.'s Models Used for this Study

INTEREST RATE MODEL

AD&Co.'s library of term structure models includes three one-factor short-rate models (Hull-White, Black-Karasinski, and Squared Gaussian including "shifted" variations) and a two-factor Gaussian model; the Hull-White model is offered by default and used for this study. Any model is instantly calibrated to a swap or Treasury curve and a matrix of at-the-money (ATM) swaptions.

LOAN DYNAMICS MODEL (LDM)

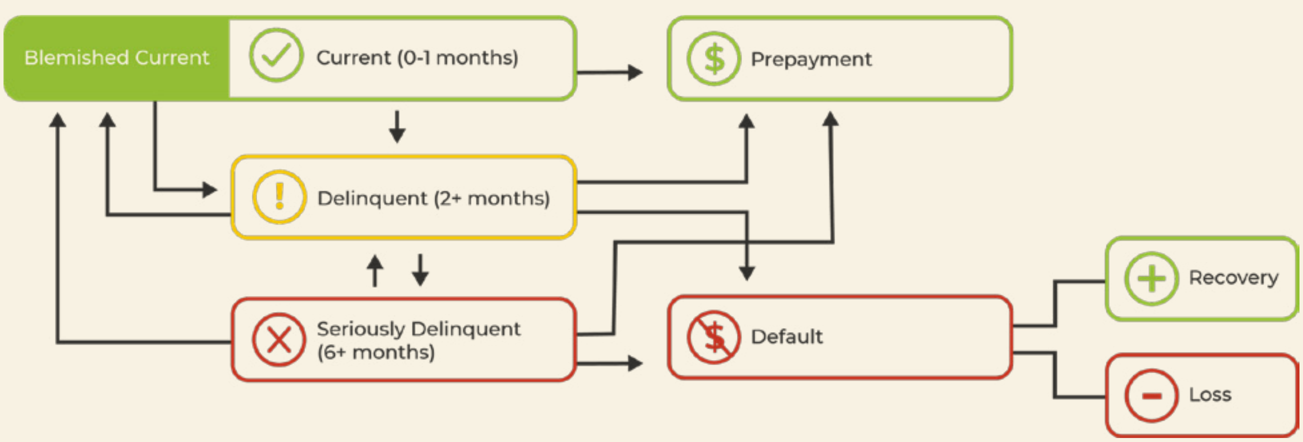
Given loan characteristics and a user-driven scenario for interest rate and house-price indices, the LDM forecasts, on a loan level or portfolio level, time series vectors for CPR, CDR, 60+ and 180+ day delinquency rates, loss severity, and cumulative loss. LDM features an open architecture that gives the user the flexibility to tune the model to better reflect the user's specific expectations regarding the behavior of their loans. LDM extends the traditional "two-state" competing risks model that forecasts only prepayments and defaults to include forecasts for a number of loan transitions as shown in Figure A1. AD&Co. has condensed the number of transitions to those which have sound economic rationale and the greatest impact on investment performance.

The model is unified across credit sector (confirming, jumbo prime, subprime, Alt-A/B, High LTV) and product type (fixed, adjustable, hybrid, IOs, first and second lien) and relies on observed loan characteristics (i.e., data available in the typical servicing system file) to make its projections. As a result, users are not required to make potentially arbitrary judgments about credit sector or product type. Users can apply the model to pools of loans containing a wide mix of underlying collateral. Key drivers are loan characteristics such as LTV, FICO, doc type, state, original loan balance, the paths of future interest rates, HPI, and unemployment. LDM is also capable of handling recent legislative/social events such as loan modifications.

HOME PRICE MODEL

AD&Co.'s Home Price Model is a non-econometric stochastic simulator. It captures a home price volatility pattern and its relationship to interest rates in a way that is consistent with empirical evidence. With the exception of interest rates, it does not relate future home prices to economic factors (which need forecasting themselves). A core model is developed from five indices: the 25-MSA Composite, Los Angeles, Miami, New York, and Phoenix. National HPA, State, and MSA level derived indices are modeled using AD&Co.'s Geographical Localizer.

Figure A1. **LDM Flowchart**



The full model includes four factors: (1) Total borrower cost including loan payment, down-payment, cost of MI, and underpriced credit risk (if any), (2) Income inflation, (3) HPA diffusion (systematic trend), and (4) HPA jump (non-systematic shocks). The ratio of (2) to (1) can be viewed as affordability index, a key driver of HPI equilibrium. The income inflation is linked to the yield curve and an unemployment factor.

Factors (3) and (4) are gauged from the actual HPA and separated by the mean of Kalman filtering. A strong (weak) historical HPA improves (deteriorates) model's forecast. Thus, the actual HPA series is a key input into the model.

The model can also be tuned to utilize the user's own HPI outlook or market median.

UNEMPLOYMENT MODEL

AD&Co.'s Unemployment Model uses home prices and a short rate as its drivers. The model is split into two components: logistic regression for unemployment's "equilibrium," and a differential equation (auto-regression) gradually moving the most recent level towards equilibrium. With slight parameter adjustments, the US model works well geographically.

The unemployment model is also utilized in the Loan Dynamics Model.

20-CREDIT SCENARIO GRID MODEL AND 3-PART VASICEK PROBABILITY MODEL

The Credit Scenario Grid contains a set of 20 engineered stress scenarios ranging from best, to base case, to worst. The Credit Scenario Grid settings are updated as needed by AD&Co. Each scenario in the grid contains interest rate shifts, home-price shocks, and dials for the integrated AD&Co. LoanDynamics Model (prepayment and default). The Credit Scenario Grid settings incorporate adverse model error in the extreme scenarios. The extreme scenarios include both economic shocks and model shocks.

These 20 pessimistic scenarios are used to forecast the performance of each loan in terms of its likelihood to prepay, become delinquent, default, and generate a loss of a certain size. Modifying standard Vasicek theory to take into account scenarios where a loan has neither a 0% likelihood of default nor a 100% likelihood of default, AD&Co. has derived a Cumulative Distribution Function (CDF) for the 20 scenarios. The results of each of the scenarios within the Credit Scenario Grid are weighted based on their marginal likelihood of occurrence. A probability weighted loss across all scenarios within the grid can be used to project the average loss (or reserve) for a loan, whereas the probability weighted loss in the chosen tail of extremely adverse portion of the distribution can be characterized as the Expected Shortfall (capital requirement). Our research shows that this three-part Vasicek approach captures the tail risk inherent in extremely adverse scenarios, which would otherwise only be simulated using a Monte Carlo approach with a vast number of paths.

CAPITAL CHARGE METHOD

In the absence of a benchmark market, the Capital Charge Method allows for computing cost of credit protection and required economic capital. As such, the method is well tailored to working with standard mortgage insurance (MI), hypothetical deep insurance, or a full government guarantee. For details of the method and its derivations, see Davidson and Levin (2014).

The formulas of the method and its inputs and outputs are shown below:

$$P = L(R)+L_{ES}(r)(R - r)IOM(R)$$

$$c = L_{ES}(r) - P$$

$$p=P/IOM(r)$$

Where:

- L is average loss
- L_{ES} is the expected shortfall (average loss in the tail at a given confidence level)
- r is relevant riskless rate
- R is target return on equity (ROE)
- *IOM* is the *IO* Multiple that is commensurate with the premium stream. The rate in parentheses is used for discounting.

The outputs from running the Capital Charge Method are detailed below:

- P — Single up-front premium
- p — Annual premium rate
- c — Economic capital

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