QUANTITATIVE PERSPECTIVES

CLIMATE-CONDITIONED LOANDYNAMICS MODEL (CCLDM)

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OVERVIEW

" Our Loan Dynamics Model (LDM) is the other main component that will account for climate risk. LDM handles the mortgage holder's behavioral response to such risk by modifying the likelihood of prepaying or defaulting."

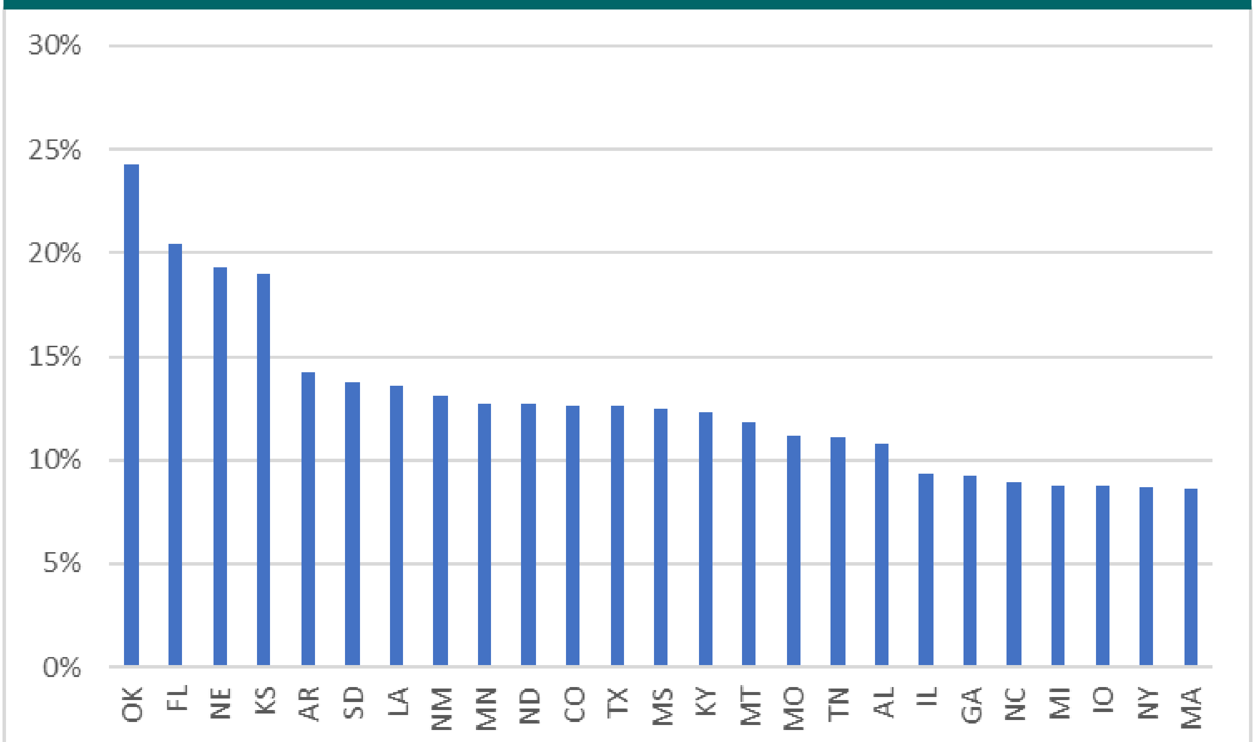
In recent articles we have described our overall approach to incorporating climate risks into our analytical framework, and provided details on how our house price appreciation (HPA) model will evolve within this framework. Our Loan Dynamics Model (LDM) is the other main component that will account for climate risk. LDM handles the mortgage holder's behavioral response to such risk by modifying the likelihood of prepaying or defaulting. Climate-conditioned versions of LDM and H{A have been integrated into our LoanKinetics (LK) tool and option-adjusted spread (OAS) subroutine and are available for general use. In this piece, we focus on how our prepayment, default, and severity models within LDM are evolving to capture the impact of climate risk.

KEY NEW INPUT: TECHNICAL INSURANCE PREMIUM

Rather than modeling individual climate events and their effects on homeowners, climate-conditioned LDM (ccLDM) quantifies climate stress through the increase in home insurance premiums resulting from increases in the frequency or severity of climate-related events. Clients will obtain these projected increases from climate data analytics firms. Such firms provide long-term forecasts of expected losses and various tail losses at the property level, given a property address. These losses are represented as ratios relative to the replacement cost of the home and are broken down by type of peril: hurricane, convective storm, flooding, wildfire, etc. AD&Co performs transformations of these inputs to create a 30-year forecast of insurance premiums, which should be viewed similarly to other economic inputs such as mortgage rates or MSA-level house prices.

Figure 1 shows the distribution of current state median homeowner's insurance premiums to mortgage payments for the top 25 states as of 2023. It doesn't include any additional policies, such as flood. It also hides considerable intrastate variability.

FIGURE 1. MEDIAN INSURANCE/MORTGAGE RATIO BY STATE



MODEL DYNAMICS

To understand the dynamics of our climate conditioning, it may be useful to think of a fixed-rate borrower as having 3 payment obligations on their property: the mortgage, the insurance policy or policies required to obtain the mortgage, and property taxes. We can think of the second and third obligations as adjustable mortgages that generally adjust upwards once a year.

Failure to pay the insurance premium can result in forced placement by the servicer; failure to pay property taxes can result in foreclosure, with the property tax claim senior to the first mortgage. For many borrowers, both the second and third payments are escrowed via monthly payments as part of the mortgage payment. Borrower sensitivity to increases in any of the components of the total housing payment is expected to be the same, since in many cases they are combined in a single payment.

Propensity

Given the vector of annualized insurance premiums (relative to replacement cost) and a current estimated replacement cost to home value (for translating these premiums to dollar amounts), ccLDM calculates each monthly insurance premium as a ratio to the borrower's principal-and-interest mortgage payment. These ratios may be adjusted for both inflations and income inflation. The Propensity Function then maps increases in these payments or "C" state, either through selling (turnover) or becoming delinquent on payments.

Dependence on CLTV

Depending on the equity position of the borrower, stressed levels of affordability are expected to result in different transitions out of the C state becoming more likely. In cases where we are not sure if equity is positive or negative (due to uncertainty in home value), the next transition being current to terminated (a prepayment, impacting the turnover component of CtoT) may be equally as likely as a current to delinquent (CtoD) transition. On the other hand, a borrower with substantial equity is more likely to turnover, while a borrower clearly in negative equity is more likely to go delinquent.

For a given month, after finding a borrower's overall propensity to exit and the split between turnover and delinquency, ccLDM generates tuning values for turnover and CtoD that apply for that month. Currently, the maximum tuning value is 2 for turnover and 2.5 for CtoD; these values take effect when the propensity to exit is 1 and all of the propensity is assigned to either turnover or CtoD.

Role of ccHPA Model

The climate-conditioned HPA model impacts the output of ccLDM in multiple ways. First, the underlying CtoD transition rate is dependent on CLTV, which is impacted by climate conditioning in the HPA model. Second, this climate-conditioned CLTV impacts the split function, determining relative likelihoods of the increased cost pressure resulting in turnover or delinquency. Finally, if the ultimate result is default, it also impacts the severity function. without a climate-conditioned HPA, none of the outputs of ccLDM would be meaningful. Appendix A shows the relative impacts of ccHPA and ccLDM on a range of loans when run through LoanKinetics.

ILLUSTRATIVE EXAMPLES

We now provide examples to illustrate the effect of ccLDM climate tunings on the projected prepayment, delinquency, and default rates for a given borrower, subject to different climate insurance and home equity scenarios. This article is focused on ccLDM: the HPA vectors used here are hypothetical and not linked to ccHPA. In a subsequent article, we will utilize the full LK implementation of our Climate Impact Suite to illustrate ccHPA and ccLDM working in tandem with one another.

Our examples involve four scenarios, all based on a geographic area in which climate effects (flood and wind) already produce extreme projected losses and high estimated technical insurance premiums, with losses rising still further over the next 12 years. One home represents a "medium risk" property within this area, while the other represents "high risk." The ratio of technical insurance premium to mortgage payment is already at 1.2 and 0.7, respectively, for these homes, rising to 1.67 and 1.04 over 12 years. For our first two examples, we treat these technical premiums as if they reflect what the homeowner is currently paying and will continue to pay; for our second two examples, we consider a situation wherein the (actual) current insurance rates are just 30% of mortgage payment, much lower than necessary for the insurance companies to remain solvent; we then increase these rates steadily over two years until they rise to the technical premium. Figure 2 illustrates the insurance to mortgage payment premiums over time for all 4 examples.

FIGURE 2. INSURANCE PREMIUM RATIO TO PRINCIPAL AND INTEREST

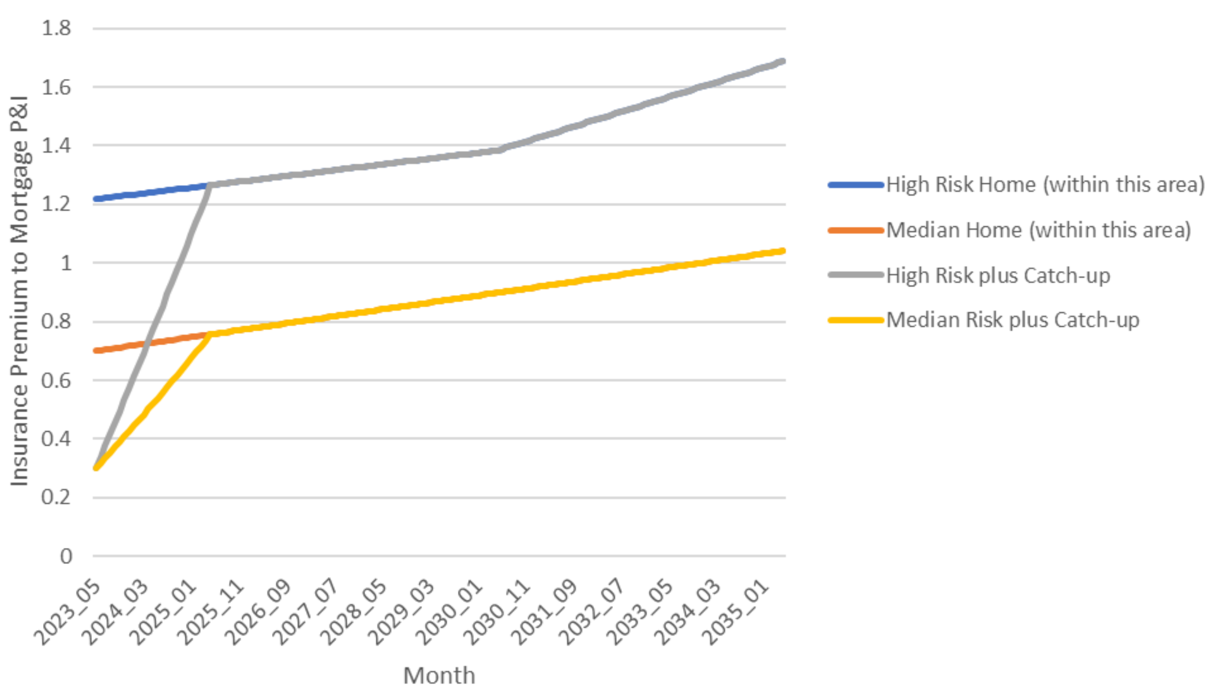


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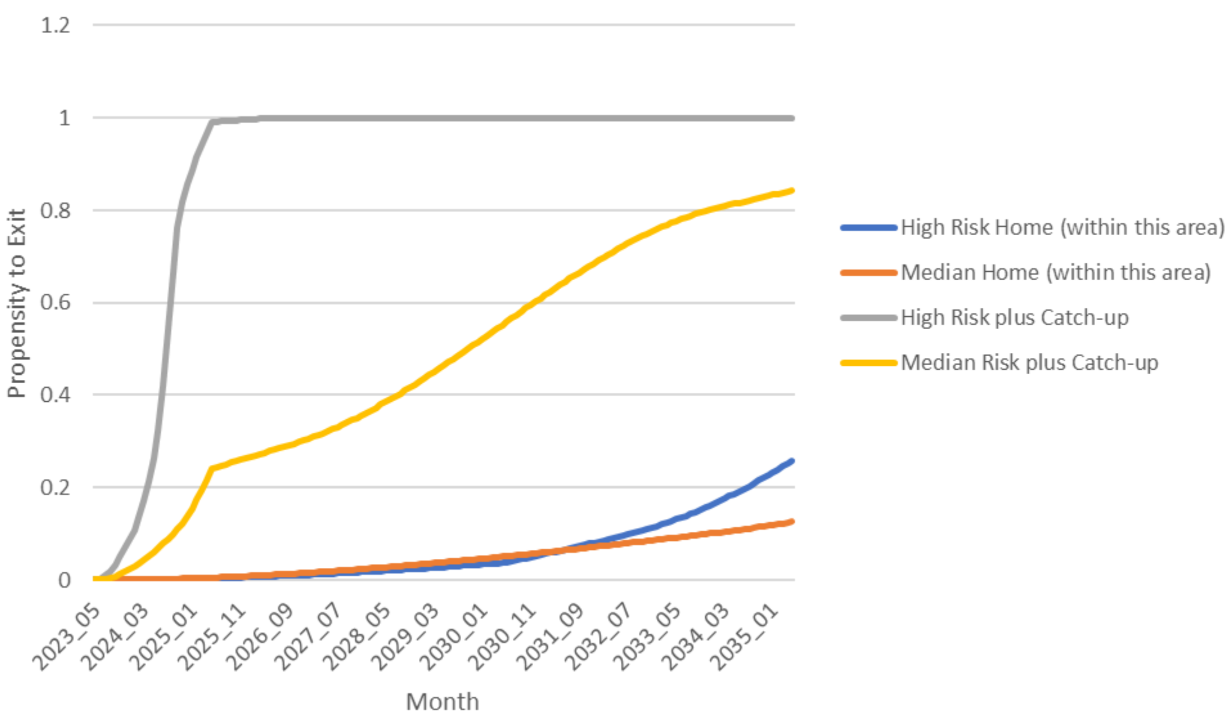
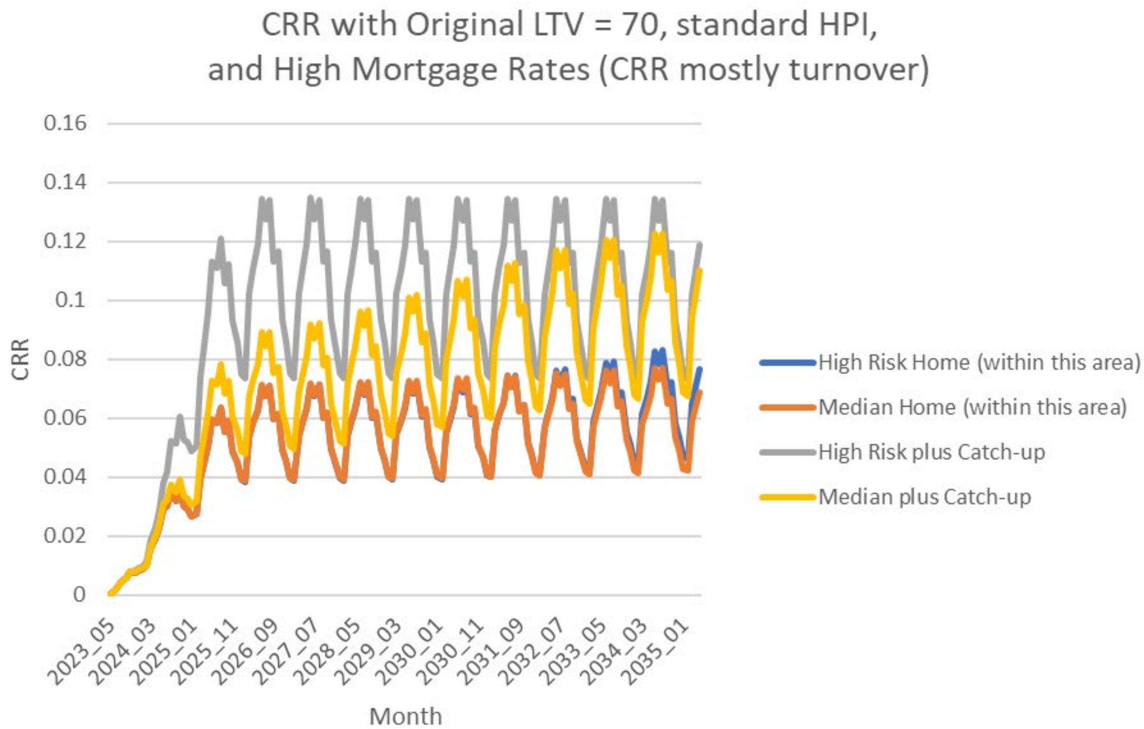
Figure 3 displays the corresponding propensity to exit for each scenario over the next 12 years. Note that this propensity is currently based solely on the increase in insurance premium that the homeowner experiences from the analysis date onward; in this framework. If the homeowner is already paying a high premium at the time of purchase, then the homeowner is assumed capable of affording it. Thus, propensity does not increase significantly in our first two scenarios, while the second two scenarios reach a propensity of 1 very quickly (high risk home) or 0.84 gradually
(medium risk home, represented by the yellow line; note that the propensity increases further outside of the 12-year window).

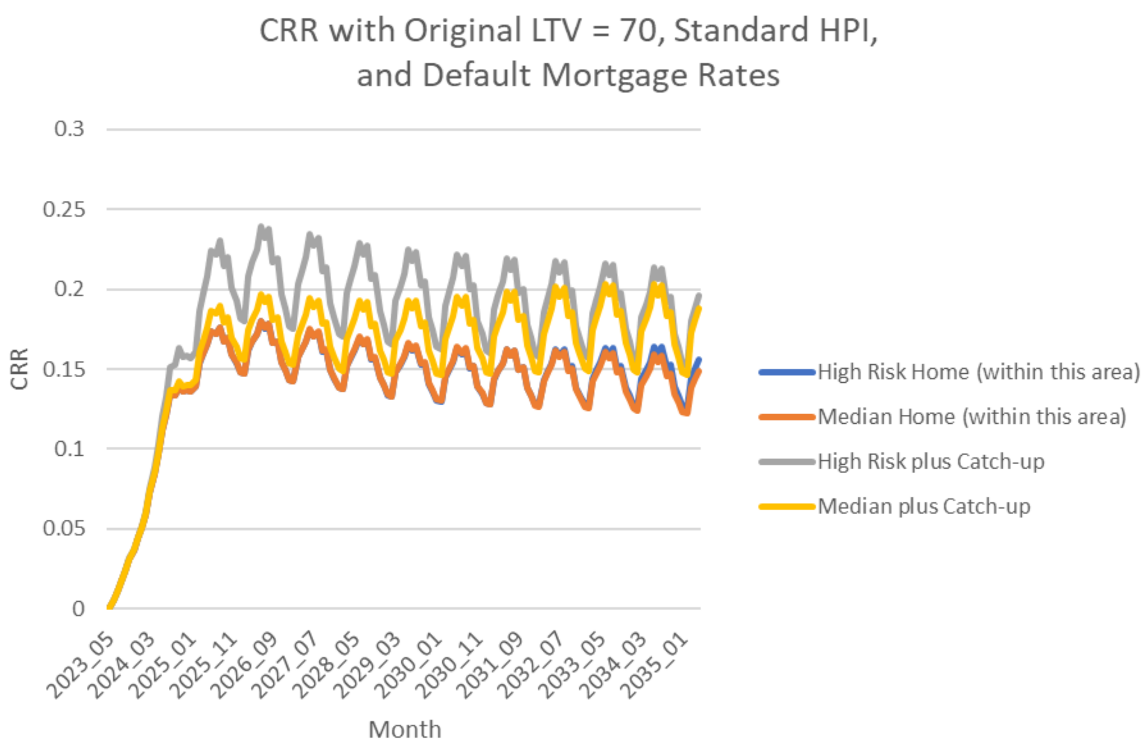
FIGURE 3. PROPENSITY TO EXIT



In Figure 4, we display the Conditional Repayment Rate (CRR) over 12 years, assuming that the mortgage holder has high equity; specifically, the CLTV remains < 80 throughout the time period. In this situation, any propensity to exit is assigned entirely to turnover, when the propensity reaches 1, the turnover tuning achieves its maximum value of 2. The first graph in Figure 4 assumes an economic environment wherein mortgage rates are extremely high in comparison with the borrower’s current rate. These high rates create a situation wherein the projected CRR is due almost entirely to turnover, so we can easily view the effect of the climate-conditioned tuning parameter over time. The second graph shows a rate scenario in which CRR includes both turnover and refinancing.

FIGURE 4. CRR GIVEN HIGH EQUITY AND TWO MORTGAGE RATE SCENARIOS





In contrast, Figures 5 – 7 display the CtoD tuning, ACtoD transition rates, and CDR for a low equity situation in which the borrower starts at 90 LTV and the projected HPA pushes the CLTV ever higher over time. Note that we used a synthetic, pessimistic HPA projection in order to create this outcome; however, for homes with very high climate risk, the ccHPA will also tend to push prices lower (and CLTV higher). In this situation, the projected default rate is already much higher than before, even for a “base insurance” scenario in which the insurance premiums hold stead. However, when the borrower is also faced with very high increases in premium, the effect is exacerbated by the propensity to exit, which here affects mainly the delinquency rates rate than turnover. Specifically, the CtoD tuning approaches its maximum of 2.5 as the propensity to exit approaches 1 and the CLTV crosses 100. Figure 7 displays the resulting ACtoD rates over time, which as previously noted, are already inflated due to the very low HPI; and Figure 8 displays the overall CDR. Note that the “climate-conditioned” component of CDR arises from the ccLDM tuning value for the CtoD transition. Figure 8 illustrates the fact that this transition does increase drastically for the “High Risk plus Catch-up” scenario compared with the lower risk cases; however, CDR is an annualized value that is also affects by other transitions such as DtoC, DtoS, StoD, etc., so the multiplicative effect of climate conditioning is not as large in Figure 9.

FIGURE 5. CLIMATE-CONDITIONED CTOD TUNING GIVEN LOW EQUITY

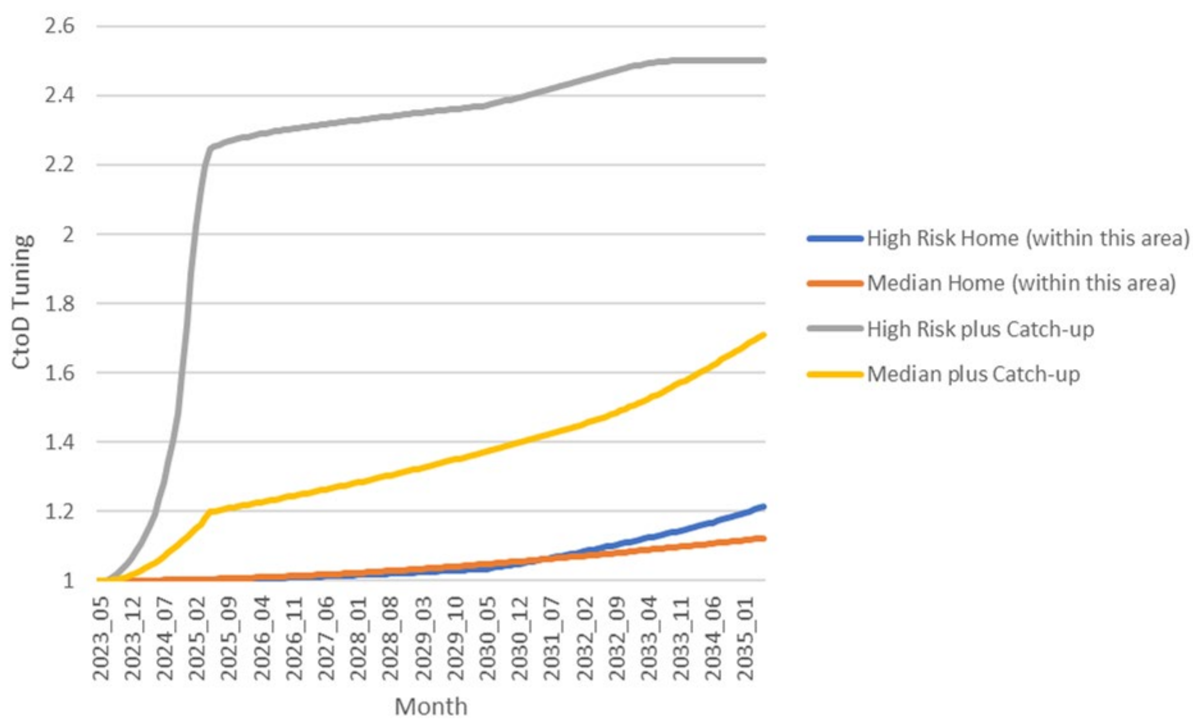


FIGURE 6. ALWAYS CURRENT TO DELINQUENT (ACTOD) TRANSITION RATE GIVEN LOW EQUITY

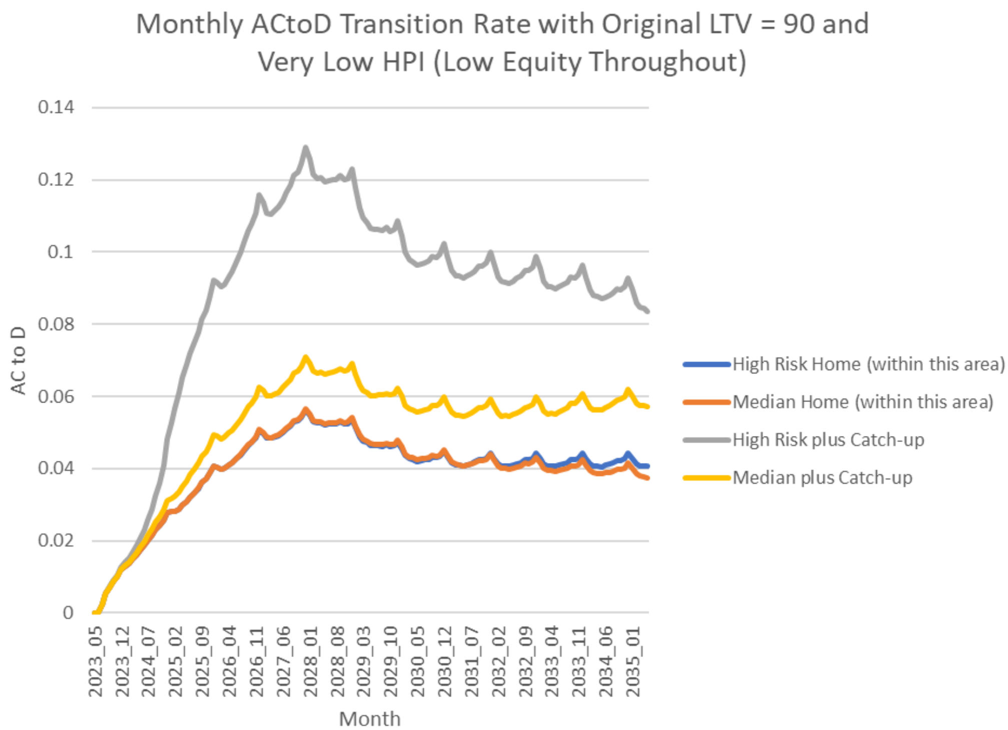
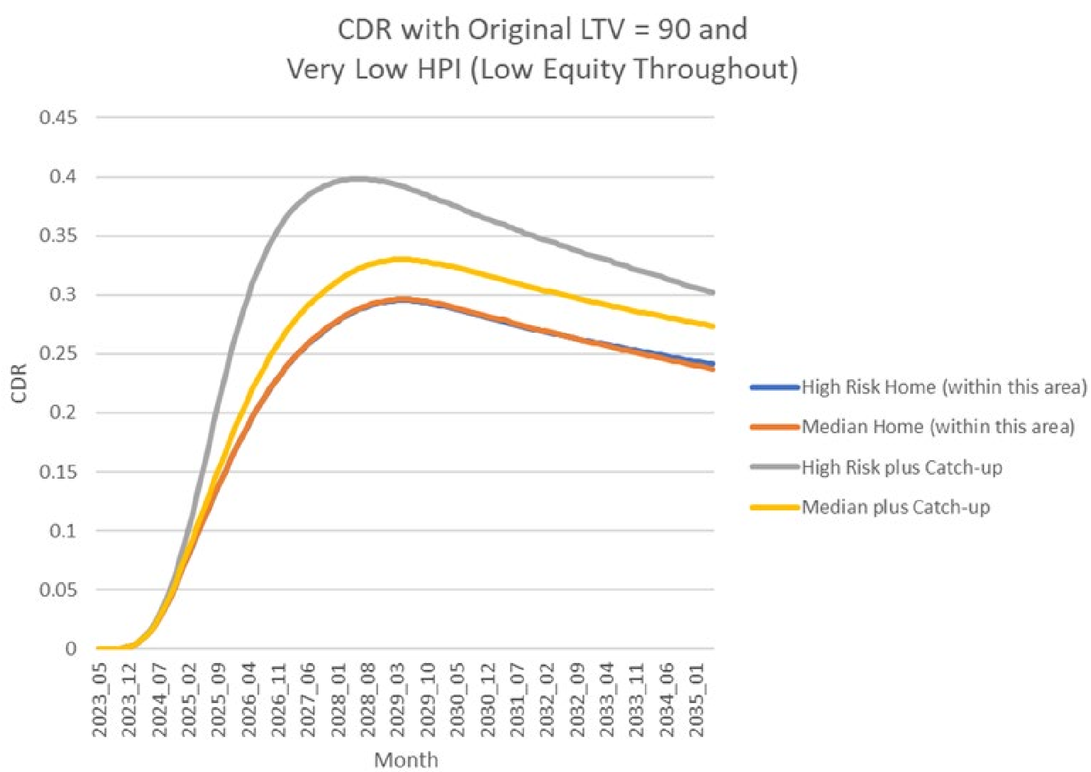


FIGURE 7. CDR GIVEN LOW EQUITY



CONCLUDING THOUGHTS

We conclude with a discussion of limitations and our future plans to surmount many of those limitations. First, our estimates for behavioral response to increasing insurance costs as a function of the size of the affordability shock are necessarily rough. The historical data on large pay shocks comes mostly from instruments such as IO ARMs and option-ARMs resetting. Those resets tend to concentrate extremely large pay shocks into a single period, whereas we are trying to estimate the cumulative impact of a wide range of significant annual increases in costs. This limitation will be mitigated over time as we obtain property-matched loan performance data for areas with distinct levels of observed insurance cost increases. Because of the reliance on ARM borrower impacts estimated during a distinct historical period (with significant borrower self-selection involved in the choice of ARM product going into the financial crisis), the response of the general population of fixed-rate borrowers to insurance shocks may differ somewhat—an additional limitation.

Second, in terms of borrower affordability the three largest components of housing cost are mortgage payments, insurance, and property taxes; we have left property taxes out of the analysis. Areas with the highest insurance increases may overlap with areas with higher rates of property tax increases (local infrastructure is as affected by climate as housing). The path to mitigating this limitation includes working with data vendors to include property taxes as part of the property-level input. Monthly utility costs may be a fourth component to consider including in the future.

Yet another limitation is that we have implemented climate conditioning via tuning. Similar to the way in which the impact of additional disclosure variables in agency pools made its way from being implemented as on-top multipliers to being "inside the function," we anticipate that climate conditioning will become more closely tied to the LDM functional forms over time. In particular, it may be beneficial to measure the size of the affordability shock relative to the borrower debt-to-income ratio rather than current mortgage payment.

Nevertheless, the way we have climate conditioned our models is a significant step forward. The framework is flexible, granular, and allows for a level of detail that does not yet exist in the realm of climate risk analytics for mortgage loans and securities. As climate models themselves evolve, improve, and provide information on a wider range of phenomena, our framework is well positioned to capture the link between borrower costs and behavioral responses.

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APPENDIX A: RELATIVE IMPACT OF CCHPA AND CC LDM

The first table shows the contribution of ccLDM to the total increase in cumulative loss under scenario 7 (our base case scenario in our scenario grid methodology) for an extreme TIP increase scenario (one which is expected to apply to somewhat less than 5% of the most impacted properties). In many cases, in a benign HPA environment ccLDM mitigates increases in cumulative loss due to heightened turnover.

Loan(LTV_FICO)	Scenario	ccLDM Share
65_600	7	-70%
65_690	7	-83%
65_770	7	-84%
70_600	7	-64%
70_690	7	-77%
70_770	7	-79%
75_600	7	-58%
75_690	7	-71%
75_770	7	-74%
80_600	7	-38%
80_690	7	-55%
80_770	7	-61%
85_600	7	18%
85_690	7	5%
85_770	7	-3%
90_600	7	32%
90_690	7	20%
90_770	7	12%
95_600	7	39%
95_690	7	29%
95_770	7	23%

The second table shows the same contribution for the same TIP scenario, but for scenario 13 in our scenario grid, which is roughly a 95% stress scenario for HPA. Under a dire HPA scenario, ccLDM tends to account for between 38% and 67% of the increase in cumulative losses due to climate conditioning in extreme insurance scenarios.

Loan(LTV_FICO)	Scenario	ccLDM Share
65_600	13	59%
65_690	13	61%
65_770	13	61%
70_600	13	61%
70_690	13	63%
70_770	13	65%
75_600	13	60%
75_690	13	63%
75_770	13	66%
80_600	13	58%
80_690	13	62%
80_770	13	67%
85_600	13	52%
85_690	13	58%
85_770	13	66%
90_600	13	44%
90_690	13	52%
90_770	13	64%
95_600	13	38%
95_690	13	46%
95_770	13	61%

Together, these tables emphasize our point that a unified approach that includes climate conditioning of both HPA and behavioral models is essential.

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APPENDIX B: RECENT EMPIRICAL EVIDENCE

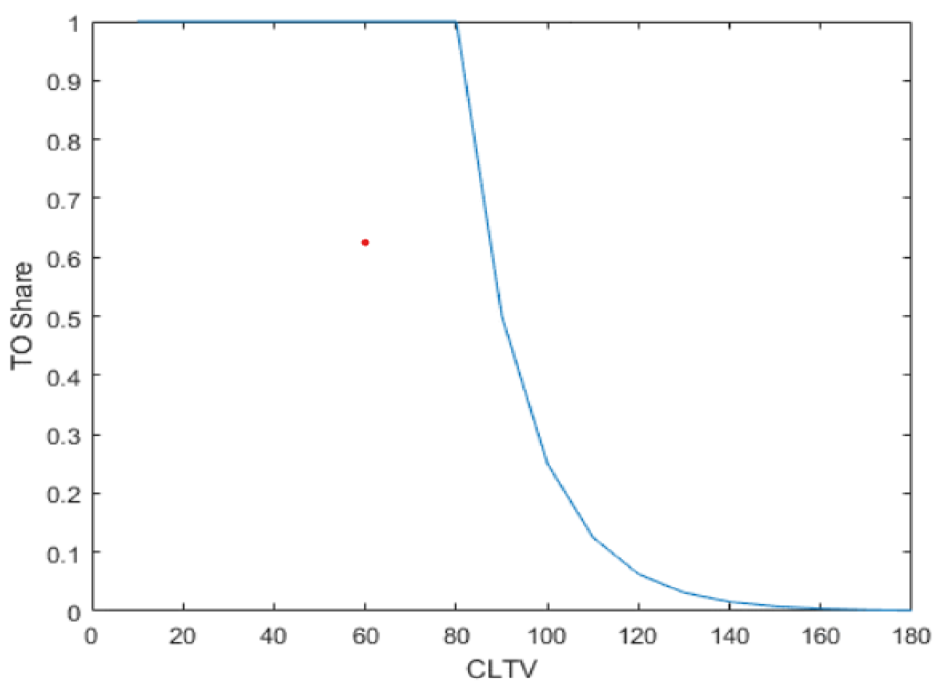
Our Climate Impact Suite incorporates the impact of rising climate-related risks, as transmitted via rising insurance premiums, using two channels: behavioral changes, accomplished by “climate conditioning” our Loan Dynamics Model (ccLDM) and changes to our house price appreciation (ccHPA) model. In contrast to most of our models, we added these effects based on sound theory and economic rationale, expecting to observe the impact of rising insurance premiums in data in the near term. In this section, I discuss the theory, rationale, and accumulating empirical evidence that both types of alterations are sound. I conclude with a section on the challenges of performance tracking for climate-conditioned models.

Economic Rationale

For climate-conditioned LDM, we used the effects of payment shock—as measured on ARM borrowers through the financial crisis—to estimate the likely impact on delinquency and prepayment propensities. The underlying reasoning is that borrowers should behave the same whether a given housing payment shock occurs due to a mortgage coupon increase, an interest-only loan enters its amortizing period, or a significant increase in insurance premiums occurs. In many cases, there is a single monthly payment that is escrowed by the servicer, and what ought to matter is the size of the increase relative to current payment (and other payment obligations).

The transmission of this shock was allocated across delinquency and prepayment propensity based on CLTV. The reasoning in this step is that once housing cost reaches an unaffordable level, if their CLTV permits a sale, borrowers would generally prefer to sell their property and move rather than go delinquent, as is reflected in higher turnover. Figure 1 shows the share of propensity as a function of CLTV allocated to turnover.

FIGURE 1. TURNOVER PROPENSITY AS PROPORTION OF OVERALL PROPENSITY BY CLTV

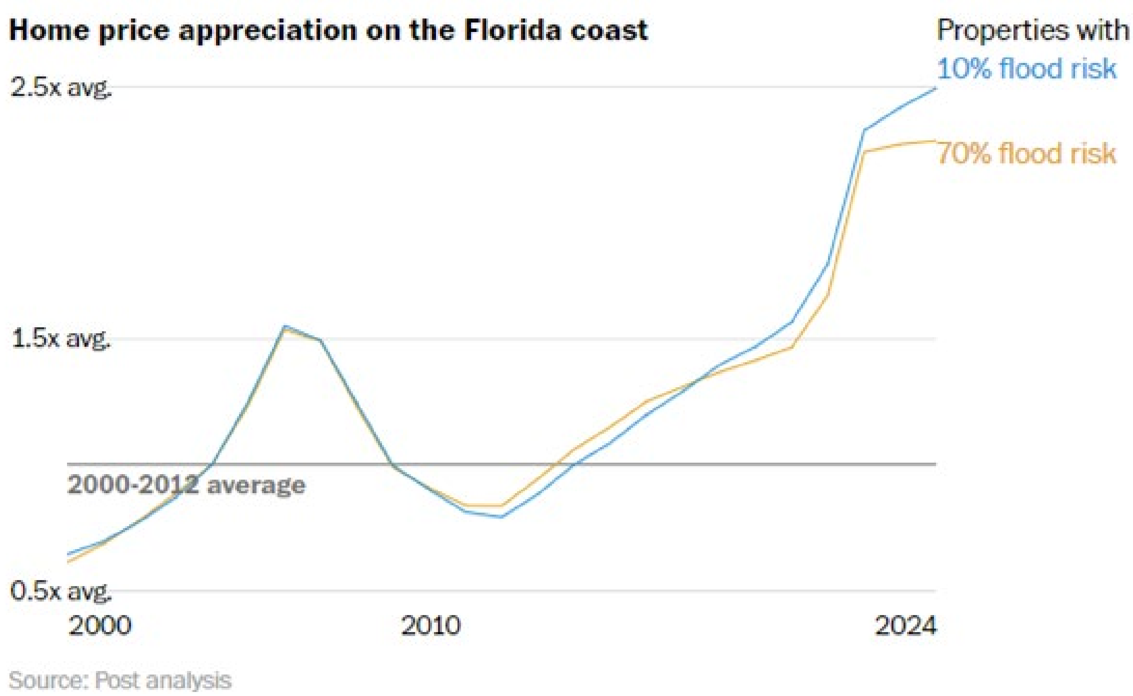


For the impact on property prices, our reasoning was similar: the downward impulse to HPA from an increase in costs due to insurance should be the same magnitude as if that increase in cost occurred due to an increase in mortgage rates. Fortunately, our HPA model already has the contribution of mortgage rates as a feature. While mortgage rates are a systematic factor affecting all loans in a portfolio, we needed to introduce the impulse due to insurance shocks as a loan/property-level feature.

Recent Empirical Evidence

On October 15, 2024, the Washington Post published an article entitled "Where Climate Change Poses the Most and Least Risk to American Homeowners," which contains the following chart (based on an analysis of 2 million home sales in Florida since 2000).

FIGURE 2. IMPACT OF FLOOD RISK ON OBSERVED HPA IN FLORIDA



The *Post*'s analysis compared properties in the lowest decile of flood risk with those in the 7th decile and observed that price appreciation began to diverge between the two groups only in the last few years. The higher flood risk properties show no appreciation during a period of high appreciation for low flood risk properties. [1]

[1] See https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4192699 for another analysis measuring the impact of rising flood insurance premiums on real estate transaction prices.

On the prepayment and delinquency propensity side, we are also beginning to see empirical studies linking insurance premium increases to higher turnover and delinquency propensities. Ge et al. find a relationship between an increase in insurance premiums and increases in both delinquency and prepayment propensity.[2] Their measured mortgage delinquency effect is greater for higher loan-to-value mortgages, while the prepayment effect is smaller for these loans.

We therefore can find early empirical validation of both our postulated insurance premium to house price appreciation relationship, and the positive association between higher rates of premium increase and both increased turnover and delinquency propensity. Additionally, the second paper validates the CLTV dependence we postulated.

Challenges to Performance Tracking

A simple state- or MSA-level analysis tracking behavioral model residuals, or HPA trends, relative to measures of insurance premium increases, while interesting, suffers from limitations in ability to provide insight into how well our models are measuring turnover/delinquency and property value response to insurance premium shocks.

First, state- or MSA-level HPA dynamics depend on a host of other factors. For example, during the pandemic, Texas and Florida saw a boom in migration, followed by a surge in supply, while other states (such as New York) saw limited increases in supply. As that supply comes on line, we can expect house price increases in Texas and in Florida to subside, independent of any insurance affordability shocks. That many of the locations with the most supply coming online also happen have among the highest insurance cost increases confounds the analysis.

Second, even within states or MSAs there is considerable variability in insurance costs based on proximity to the coast or other bodies of water, elevation, and year built (later code years tend to result in lower premiums and lower severity exposure). The appropriate granularity of performance tracking for HPA appears to be property level (while we have traditionally been set up for MSA-level HPA analysis). However, actual property valuations are only observed when a sale occurs (even MSA-level reported data from FHFA or other sources involves a fair amount of repeat-sales model based interpolation). This means the potential wait to observe property-level value impacts can be long, and we may still be left with observing MSA-level HPA indices (which are constructed, not observed, values) for earlier indications of HPA impact.

For behavioral models, our performance tracking already occurs at the loan level. However, we also need to observe insurance premium shocks at the borrower level and tie this data to the loan data and property data to observe true climate-conditioned HPA (which drives CtoD in the base model, along with the additional impact from insurance premium shocks).

[2] Ge, Shan, Stephanie Johnson and Nitzan Tzur-Ilan. "Climate Risk, Insurance Premiums, and the Effects on Mortgage and Credit Outcomes," (October 18, 2024). https://ssrn.com/abstract=4992281

Finally, both of these issues involve PII concerns, since property address would be a required field. Nevertheless, given the importance of measuring rising climate-related risks, and especially the potential impact of the underpricing of insurance in higher-risk locations and significant premium increases as they are corrected, it is better to release a model that can be used for stress testing and preliminary risk and pricing analysis. Loan-level performance monitoring can be set up at the user level, avoiding the exchange of fields with PII.

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