MIAC ANALYTICS

MIAC Perspectives

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Table of Contents

Introducing the Updated CORE™ Residential Models for Credit, Prepayment, and Loss

Introduction and Summary

Over the past two years, MIAC's Borrower Analytics Group has completely revamped the CORE™ family of Residential Behavioral Models. These models cover all three residential sectors: Agency, GNMA, and Non-Agency and include the following components:

- Credit frequency (i.e., "roll rates")
- Voluntary Prepayments
- Foreclosure/REO Timelines
- Loss Severity (i.e., Loss Given Default)

Together, these model components provide a complete probabilistic description of all possible outcomes for a given loan at every projection month. These models have been implemented into Vision™ and WinOAS™, our two primary asset valuation solutions. In addition, the data normalization and missing value imputation challenges have been addressed with DataRaptor™, our extract, transform and load (i.e., ETL) software solution.

MIAC's Borrower Analytics Group has extensive prior experience in model development and model validation at leading investment banks and CCAR commercial banks. We adhere to a disciplined and rigorous model development process. These development phases include (1) data preparation and exploratory data analysis, (2) feature/explanatory factor definition, (3) model specification and estimation, (4) parameter review, (5) software implementation, and (6) replication testing.

This process is designed to satisfy the regulatory requirements of SR 11-7 as well as conform with industry best practices regarding model risk management.

The purpose of this report is to highlight the six primary features which distinguish these behavioral models. They include:

- An exhaustive set of explanatory variables
- Incorporation of all relevant macro-economic factors
- Detailed loan status tracking throughout the life of the loan
- A highly granular and macro factor-dependent foreclosure/liquidation timeline model
- A state-of-the-art loss severity model that is fully integrated with the frequency model
- Sub-models that capture distinct intra-sector and product-specific behavior

In forthcoming issues of *MIAC Perspectives*, we will elaborate on each of these features in much greater depth, provide conceptual and empirical support for our approach, and demonstrate the quantitative impact on outcomes for both MSRs and whole loans.

Feature 1: An Exhaustive Set of Explanatory Variables

All of our models were estimated using the best loan-level data available for that particular sector. Our estimation process considered a large set of potential explanatory variables based on data availability, industry and academic research, and prior experience.

The ideal dataset for a particular sector has all available attributes (i.e., fields), a rich cross-section of those attributes (e.g., a broad range of FICOs, DTI, etc.), and a long history through various economic cycles. However, all datasets have limitations. For example, the GNMA loan-level disclosures have a large set of attributes but a very limited history: the observations start in 2012. Importantly, the GNMA data does not include the financial crisis where mark-to-market combined LTVs (hereafter, CLTV-MTM) reached 200% and higher.

We address these limitations by using both primary and secondary (or supplemental) datasets for each model. For example, the GNMA loan-level disclosure data is the primary dataset because this has the largest population of distinct loan attributes. However, this primary dataset is supplemented with the Agency loan-level data – whose history covers the financial crisis. This secondary dataset enables us to inform our estimation of loan behavior in the high CLTV-MTM region.

The above example shows how we enrich the GNMA data to supplement an observation period deficiency. We also use secondary datasets to supplement missing attributes. For example, we use the co-borrower field in the Agency data to inform our estimation of this effect in the non-Agency model.

Figure 1 provides an overview of the variables included in our CORE Family of Residential Behavioral Models. We also indicate whether or not the cross-section of our behavioral model competitors also includes that explanatory variable. As is evident, our models make use of a larger set of factors than typical competitor models. And as we show below, these additional variables make our predictions more precise.

Attribute	Competitors
Borrower	
Co-borrower (Y/N)	
Debt-to-income	Y
Documentation	
FICO	Y
Occupancy (Primary, Second, Investor)	
Purpose (Refi, Purchase)	Y
Economic and Rates	
Home Price Appreciation	Y
Rate Incentive	Y
Refi Burnout	Y
Unemployment change	

Attribute	Competitors
Loan and Property	
Amortization Term	
Anti-deficiency	
Balance	Y
Channel	
HARP eligible?	
Hybrid: rate reset	
IO: re-cast	
Lien Position	
Loan age	Y
LTV	Y
Months-in-state	
State/GEO	Y
Vintage	Y
Previously Modified and Payment Change	

Figure 1: CORE Model Variables

Although a comprehensive set of explanatory variables results in much higher precision, it also requires a much more extensive data management effort to prepare a portfolio for analysis. Otherwise, the advantages of a more sophisticated and accurate model will not be realized. This data preparation effort includes data scrubbing, data normalization, and imputation of missing values. MIAC has 30-plus years of experience handling large sets of mortgage loan-level data. We have the software, reporting, and customer support to handle large, irregular, and otherwise challenging client data. As one important example, we supplement these behavioral models with missing value models which optimally impute the expected value of missing attributes as a function of available attributes. As a result, our analytics can be run on diverse client datasets with widely disparate levels of data availability.

Feature 2:
Incorporation of all Relevant Macro-Factors

Mortgage outcomes (i.e., defaults, prepayments, foreclosure timelines, and loss severities) depend upon both attributes observed at (or near) origination (like DTI, FICO, and CLTV) as well as the evolution of macro-economic factors (like mortgage rates, interest rates, home prices, and unemployment).

Similar to many competing models, our CORE models use both primary mortgage rates and home prices to drive mortgage outcomes. Following common industry practice, we use realized historical home price indices (hereafter, HPA) from loan origination through the observation date to update the CLTV-MTM. This updated equity impacts all mortgage outcomes: prepayments, defaults, foreclosure timing, and losses. For example, higher CLTV-MTM generally reduces prepayment rates and increases default rates.

In sharp contrast to many competing models, our CORE models also use the state-level unemployment change (from loan origination through the observation date). Unemployment (hereafter, UER) and home prices (hereafter, HPA) were somewhat correlated during the 2007-2010 housing crisis, leading some researchers to conclude that HPA could reasonably proxy for “economic conditions”. However, there is no question that UER provided significant explanatory power even after controlling for HPA (via CLTV-MTM). The empirical evidence is simply overwhelming, as shown in Figure 2 below.

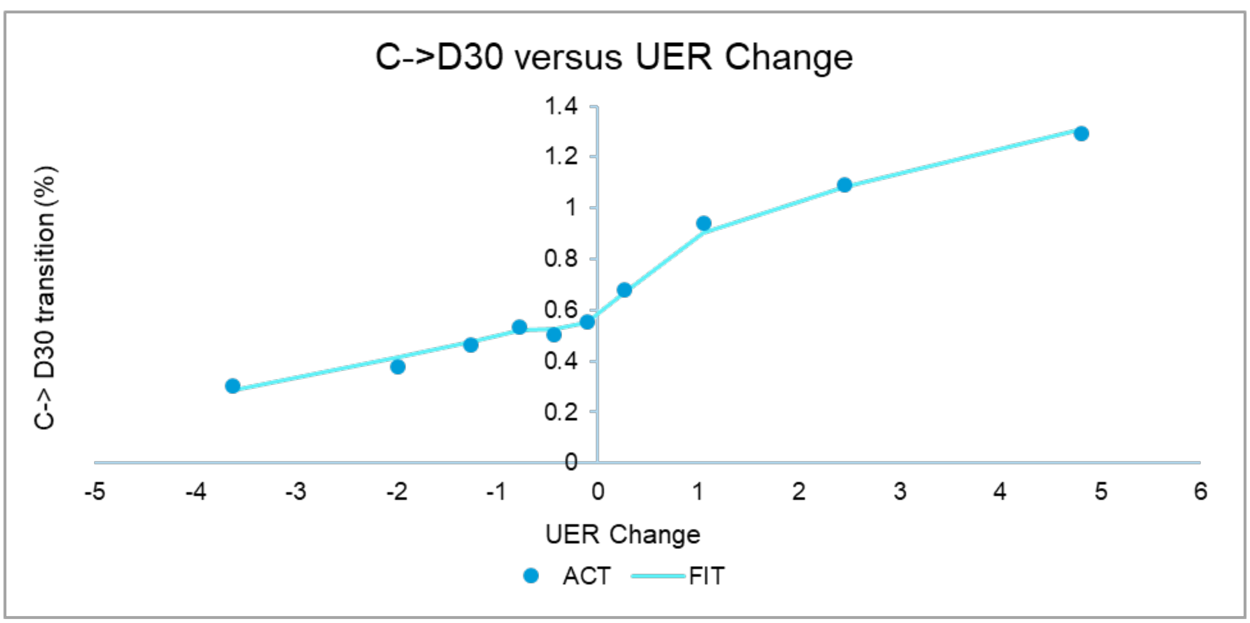

Figure 2: Impact of UER change on C->D30 Transition (Agency Fixed Rate)

Figure 2 displays the relationship between monthly Current-to-D30 transition rates (i.e., C->D30) and the change in UER between loan origination and the observation date. For example, a UER change of 2 means that unemployment increased by 2 percentage points (e.g., from 5% to 7%). As is clearly evident, increases in UER result in higher C->D30 transition rates. The results are shown for Agency data, but we find similar results for all Sectors and most transitions. Further, the marginal effect of UER is large and statistically significant even after controlling for HPA, which is handled through our econometric specification.

A few additional points merit consideration. First, Figure 2 also shows that our CORE model for C->D30 fits the data quite well. In other words, there is no systematic pattern between actuals (shown as the dots) and predicted (shown as the fitted line). Second, the current COVID-19 crisis underscores the importance of using both UER and HPA as macro drivers: UER has been very volatile, while HPA (along with other asset prices) has been increasing rapidly.

Third, we have conducted extensive additional econometric testing of numerous other potential macro-economic factors, such as disposable income and population changes. Our research shows that these additional factors do not have any marginal explanatory power. In technical terms, we have found that UER is both necessary and sufficient for explaining loan performance.

Feature 3:
Detailed Loan Status Tracking

Our CORE Residential Models provide detailed loan status tracking. We track the loan-level delinquency status from current through seriously delinquent and foreclosure. We also track assets that have transitioned to REO status, either through a completed foreclosure or through a voluntary conveyance (i.e., deed-in-lieu).

We distinguish between always current loans (or clean current) and blemished current (also known as self-cures or dirty current), as the sensitivity to attributes like FICO and CLTV-MTM are very different between these statuses. Models that aggregate these statuses will compromise accuracy for the sake of faster run-times. We believe that, in general, this is a poor tradeoff.

Our CORE model also tracks and updates the time spent in each status, which we refer to as months-in-state (hereafter, MIS). This MIS variable is a very important driver of loan performance, as shown in Figure 3 on page 5. Figure 3 is structured similarly to Figure 2. In both cases, we are plotting C->D30 transition rates for Agency loans on the vertical axis. But in Figure 3, we restrict the analysis to blemished current loans (where MIS plays a role). The actual MIS is displayed on the (horizontal) x-axis. It is apparent that MIS is a vital determinant of C->D30 transition rates. In fact, the importance of payment history is well recognized both by researchers (such as the Urban Institute and various dealers) as well as by the regulators. For example, in their recent update to the QM rule, the CFPB created a “seasoned QM” category which essentially codified the importance of this payment history effect.

The significance of MIS is difficult to overstate. The effect is large and impacts all Sectors and most transitions. Although MIS is an observable quantity at the launch date of an analysis, it must be consistently propagated in forward projections. MIAC has established a recursive algorithm that handles this updating in a computationally efficient manner.

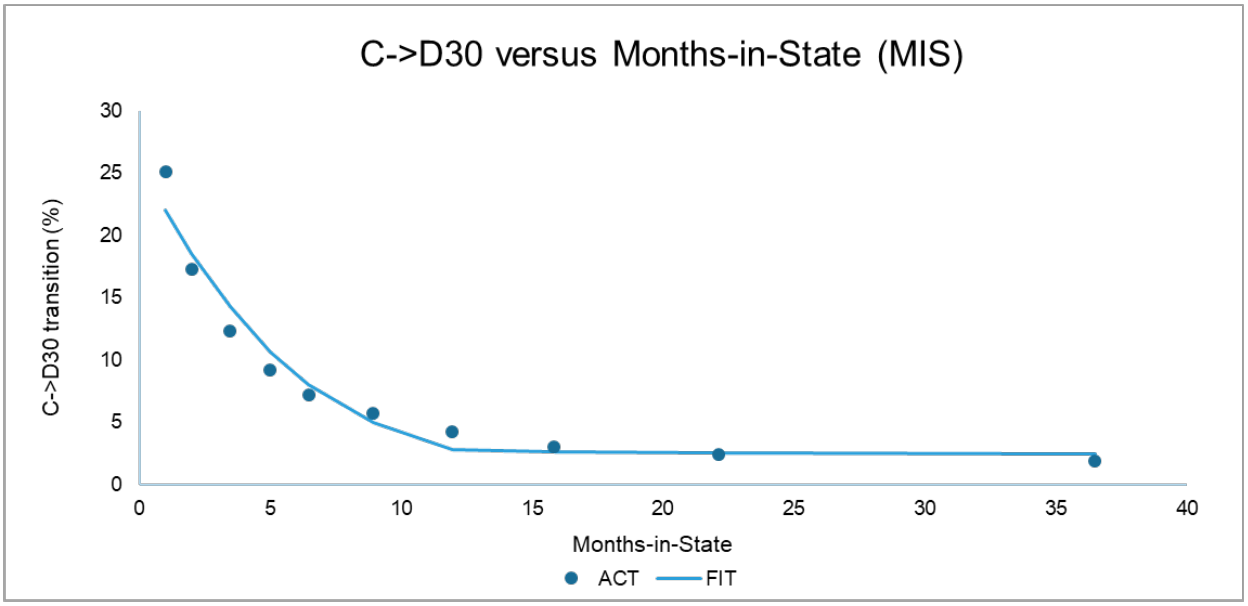

Figure 3: Impact of MIS on Blemished-C->D30 Transition (Agency Fixed Rate)

Feature 4: A Granular Foreclosure/Liquidation Timeline Model

We have also updated our treatment of foreclosure (or liquidation) timelines within the CORE Residential Model framework. Although the time from initial delinquency to final resolution of the asset is generally referred to as foreclosure timelines by practitioners, we prefer to use the term liquidation timeline. This is because our modeling approach consistently handles both the typical "foreclosure-start to foreclosure-sale to REO-liquidation" as well as more cooperative default resolutions such as short sales, deed-in-lieu, and third-party takeouts. In fact, we find that a substantial fraction of short sale default resolutions occur without ever initiating foreclosure.

Liquidation timelines are important for both whole loans (because they impact loss severities and the timing of cash flows) as well as MSR assets (because they impact sub-servicing costs, advancing expense, and reimbursement shortfalls).

Our liquidation timeline model has two distinctive features. First, it incorporates the impact of state-level geography.

It is well known that liquidation timelines in Judicial states (e.g., NY) are much longer than in Power-of-Sale states (e.g., TX). However, it is perhaps less well appreciated that there is substantial variation within each of these two categories. In fact, there is substantial overlap: the fastest Judicial states have slower timelines than the slowest Power-of-Sale states. Second, although geography plays a critical role in liquidation timelines, borrower and loan attributes also play an important role. This is because overall liquidation timelines are a probability-weighted average of various liquidation outcomes. For example, NY loans with a high probability of a short-sale resolution will have shorter average timelines than NY loans with a low short-sale probability.

Additional details regarding our approach to liquidation timelines are contained in the November 2019 issue of MIAC Research Insights.

Feature 5: A State-Of-The-Art Loss Severity Model

Our CORE Residential Model includes an enhanced Loss Severity Model, which reflects three key improvements.

First, the loss severity model is fully integrated with the default frequency and FCL timing models. That is, the transition frequency model produces an estimate of the expected months-past-due (hereafter, MPD) conditional upon liquidation for every projection month.

This expected MPD estimate is then input into the loss severity model. This seamless integration means that any attribute (or user scalar) that impacts liquidation timelines (e.g., the geographical location of the property) will automatically impact loss severity. In other words, the function of the severity model is to predict losses given liquidation timelines, while the role of the frequency model is to predict the liquidation timelines. This is precisely analogous to the way a prepayment model works. Namely, it predicts prepayments conditional upon a given realization of primary mortgage rates. Primary mortgage rate projections (either static or OAS-based) are external to the prepayment model itself.

As a recent example of the interplay between timelines and loss severities, consider the Federal CARES Act promulgated in response to COVID-19 enacted in March 2020. Under the provisions of this act, federally backed mortgage loan servicers (including those servicing conventional Agency loans) were prohibited from initiating any foreclosures for a 60-day period starting March 18, 2020. The cash flow and impact of this act were quantified within our model framework by reducing (to zero) the probability of migrating from Seriously Delinquent to REO for two observation months. As expected, this increased expected MPD and hence loss severities.

The second enhancement of our new severity model is that it is developed and estimated at the component-level. That is, we have separate estimations for the property loss and three major expense components:

Taxes and Insurance, Maintenance, and Legal. This component-based approach has several advantages. First, component-level estimation is much more straightforward. Second, component-level outcomes give users more flexibility to perform “what-if” prospective analyses. For example, if prospective property taxes increase in a jurisdiction, model users can easily adjust the appropriate coefficients and quantify the impact on their portfolio. A final advantage is that it is easier to extend the model - estimated on Agency loss data - to other Sectors. For example, losses on FHA loans can be analyzed by applying a reimbursement shortfall to the legal component of total losses.

The third and final enhancement regarding the updated loss severity is the introduction of additional explanatory variables. For example, we find that loan purpose is an important driver of loss severity: purchase loans are less likely to have appraisal bias. As a result, they have lower severities than refinances, holding all other factors constant. It is plausible that the appraisal reforms included in Dodd-Frank will reduce “appraisal shopping” and hence the magnitude of this effect. However, we plan on waiting for more evidence to accumulate before we modify this effect in our model. Also, we include variables that enhance predictive accuracy even though the causal mechanism is indirect. As an example, we find that higher FICO scores result in lower loss severities, primarily through the property loss component. We attribute this to higher FICO borrowers taking better care of their properties as well as a higher percentage of cooperative resolutions, such as borrower-titled short sales.

Feature 6: Sub-Models that Capture Distinct Intra-Sector and Product-Specific Behavior

The final distinguishing characteristic of the CORE Residential Model is that we distinguish default and prepayment behavior both across and within sectors. For example, within the GNMA sector, we find that FHA loans have worse credit than VA, even after adjusting for observable attributes like DTI, FICO, and CLTV-MTM. And VA prepayments are much more sensitive to rate incentive versus FHA prepayments, especially between 6-10 months WALA. Within non-Agency, we find that non-QM loans require their own sub-sector model. In other words, even after adjusting for the large set of observable characteristics displayed in Figure 1, non-QM loans have worse credit, faster base case speeds, and lower refinance sensitivity.

Even within a sector or sub-sector, we have product-level differentiation where necessary. As an example, we find that non-Agency Hybrids have higher C->D30 transition rates than non-Agency Fixed Rates, even before reset and after adjusting for observable attributes. This is especially true of the short-reset Hybrids that were ubiquitous before the financial crisis.

Conclusions

The release of the CORE family of residential behavioral models represents an important milestone for the industry, for MIAC, and most importantly for our clients. These models are important drivers for both whole loans and MSRs, and all applications: valuation, risk sensitivities, stress testing, CECL, and beyond. Borrower behavior projected from CORE models are highly intuitive and robust in both base case and stress scenarios.

These models have been integrated with granular cash flow engines and are facilitated by the most robust data handling tools available in the industry. They provide users with the ability to precisely quantify the implications of specific loan attributes and macroeconomic scenarios across a diverse set of Residential assets.

These enhanced models will enrich valuations and risk metrics for software, valuation and hedge advisory clients.

Dick Kazarian
Managing Director, Borrower Analytics Group

2020 Market Retrospective

COVID-19

Prior to COVID-19, unemployment was at a 50-year low and inflation was also below the Fed's target of 2.0%. A significant portion of the U.S. economy closed and remains closed due to COVID-19. Real GDP growth fell during the second quarter by a nearly unprecedented 31.4%, numbers that we have not seen since the Great Depression. This directly impacted mortgage performance in ways that we could have never imagined.

In March, the Mortgage Credit Availability Index contracted by an average of 16.1% across all mortgage classes – reflecting increased risk aversion within the mortgage industry. The shutdown of industry, manufacturing, and retail, with no end in sight, created a great deal of uncertainty which caused capital markets to freeze up. This caused the government to step up and inject liquidity into the economy via the CARES Act. Current mortgage deferral rates are continuing to improve, down to 5.4% in total, or 2.7 million mortgages, except for very specific geographies where the shutdowns are more pervasive.

COVID-19 deferrals and the restriction on delivering loans that were not contractually current caused a temporary bottleneck in production for many originators. Fortunately, the GSEs moved quickly to resolve the issue by restoring liquidity during this challenging time. The ability of workers to work remotely provided opportunities and increased demand in secondary housing markets. This also fueled the moving economy, home sales, and of course, mortgage demand.

Non-QM

The disruption in March caused many originators to either shutdown operations, face margin calls, or markdown their books in an adverse fashion. The lack of non-QM capital markets has contributed to the lowest levels of credit availability since 2015. This is largely attributed to the higher funding costs, increased defaults, and the likelihood of continued forbearance.

Non-QM 2.0 issuance has begun to ramp up production slowly, like in 2014 when the product was primarily originated by depositories and sold to insurance companies and pension funds. The majority of current non-QM production is much higher quality: 24-month bank statements, higher minimum FICOs, and lower maximum LTVs.

Delinquency rates on 12-month bank statement (BS) loans spiked to much higher levels than delinquency rates on 24-month BS loans earlier this year, in part because the CARES Act helped employees much more than the self-employed, which are overrepresented in the 12-month BS programs. In fact, research from the Becker Friedman Institute at the University of Chicago found that between April and July 2020, 76% of workers eligible for regular Unemployment Compensation were eligible for benefits that exceeded lost wages. We expect that loan officers will continue to focus on higher balance and high credit quality Agency loans and FHA/VA streamlined refinances over the near term.

This is because, in light of the loan officer compensation rules promulgated as part of Dodd-Frank, MLOs cannot be compensated at a higher rate for the more difficult loan programs. However, as the population of these easier-to-originate loans get refinanced, loan officers will turn their attention back to non-QM originations to maintain volume.

Non-QM loan performance is driven by many of the same factors that drive Jumbo, Agency, and FHA/VA performance. For example, DTI, FICO, LTV, and SATO are big drivers of credit performance. Similarly, age, balance, refinance incentive, and burnout are important drivers of prepayments.

However, MIAC's research has found that originator and servicer play a much more important role in non-QM credit performance than in Jumbo and Agency. Also, our research has found that non-QM prepayments have very different aging profiles than those found in other sectors. This is because a significant segment of the non-QM market is effectively bridge loans. Once the Agency Bankruptcy or Foreclosure seasoning requirements are met, non-QM borrowers will refinance out of their non-QM loan into an Agency loan on much more favorable terms. This is particularly important for conforming balance non-QM, which form the bulk of the sector. MIACs has developed specialized non-QM collateral models, deployed in our Vision platform, to capture this sector-specific performance.

Scratch and Dent (SD)

The Scratch and Dent market for Agency kickouts loans has been robust in 2020, driven largely by the tremendous volume of new originations. With pressure to close loans on time, the challenge of on-site appraisals, and the disruption caused by the shift to remote work amongst mortgage originators, the defect rate has increased. The large volume of purchase transactions, which tend to have higher DTIs and higher LTVs, can lead to greater performance, appraisal, and income defects.

Fortunately for sellers, SD demand is robust, and pricing is as strong as it has ever been. This pricing, combined with very low interest rates which limit the availability to cure the defect, has created a situation where the best execution is often a loan sale.

GNMA Early Buyouts (EBOs)

GNMA EBOs have become one of the most desirable alternative asset classes, as many of the large funds who had been buyers of non-QM are now exploring other asset classes to deploy capital. The risk/yield relationship is very attractive to this buyer base. Despite several very large sales this year, it has been difficult to satisfy the market. We have seen that the complexity of these transactions and disposition has been underestimated by some accounts as they wade into the universe of government regulations.

The competition for these loans has driven prices to levels we have not seen since a very brief period in late 2018 when a potential HUD auction was circulating.

EBO pricing has largely been dependent upon the size of the offering, with the larger deals (e.g., >50 million), receiving markedly better bids, centering around par. The volume of this trade has started to contract recently, largely due to COVID-19 relaxing and greater certainty regarding borrowers' futures. MIAC is active in the EBO space and currently provides monthly valuations of nearly 20 billion GNMA across a range of clients.

Non-Performing Loans (NPLs)

Pricing has improved to levels not seen in recent years, largely driven by demand, lack of deals, and more capital chasing these yields in whole loans. With the contraction in the non-QM market, many funds were left with capital to deploy, and NPLs provide an attractive risk-adjusted yield. As originators have had record years, there has been less bandwidth to do anything other than originate. These gains in new origination this year are a great tool to offset any losses that may be realized in a non-accrual sale.

There are numerous sources of uncertainty impacting the volume and pricing of NPLs. First, policy risk exists in terms of the size, timing, and terms of additional Federal stimulus legislation which will impact the ability of borrowers to make timely payments. Importantly, new legislation could easily advantage wage earners over self-employed borrowers, which would further bifurcate the credit performance we witnessed earlier this year. The second source of policy risk is foreclosure and eviction moratoria which can be enacted and extended at the federal, state, municipal, and program levels. For example, all properties secured by VA-guaranteed loans are subject to a foreclosure and eviction moratorium through February 2021, which was originally set to expire in December 2020. Third, a new administration with an emboldened CFPB could easily impose additional servicer mandates that raise costs and extend timelines.

The pace of economic recovery will also impact the population of borrowers who can re-instate or otherwise cure, and the level of rates will impact the availability of payment-reducing modifications.

Looking ahead to 2021 and beyond, there is likely to be a flood of NPL loans into the marketplace. Combined with additional supply in the non-QM market, we expect that gains in NPL pricing experienced in 2020 will abate or even reverse. And faced with the extended time frames and expensive servicing obligations, a sale is often a more compelling option, especially if in-house default servicing capacity does not exist.

Any serious analysis of NPL valuation and risk needs to accurately forecast the frequency and timing of borrower reinstatement, liquidation timelines, and loss severity given default. MIAC's CORE™ Residential Model Suite provides a comprehensive and consistent framework that accommodates each of these features, as we have discussed in recent CORE webinars. As highlighted in these presentations, the above model components are fully and consistently integrated. As an example of this integration, any increase in liquidation timelines (e.g., due to a foreclosure moratorium) will automatically increase loss severities due to increased tax and maintenance expenses.

For more details regarding our framework for Liquidation Timelines, see our November 2019 issue of MIAC's Research Insights Series.

Outlook for 2021

The impact of COVID-19, from a macro perspective, as it affects both employment and the economy, but also the mandated forbearances in the mortgage space, will continue through mid-2021 at a minimum. The political climate will likely lead to additional availability of mortgage forbearance programs, at least through Q1 and likely Q2.

Once forbearances run out, there is a limit to what servicers and taxing authorities can afford to float, some percentage of these loans will ultimately default. Will the overhang of deferred balances impact the mobility of borrowers who may need to move to find new employment? This is just one question that will need to be addressed.

On a macro level, there are simply some borrowers who will have challenges in resuming payments, perhaps their employer was a victim of COVID-19, or other factors affect their ability to pay. These loans will likely convert to non-accruals and continue down a path to REO. This will create a burden on mortgage insurance companies and GNMA that will ultimately trickle up into the broader mortgage financing market, impacting all borrowers to some degree.

The bright spot in the mortgage market is that there is sufficient capital waiting to be deployed at the right time. That may come when forbearances end, when there is clarity in the economy, or when the judicial risk in certain states is better understood. The largest challenge in this economy is simply uncertainty. If a vaccine eases this, or if additional taxpayer bailout monies are made available, liquidity can only improve.

Brendan Teeley
Senior Vice President, Whole Loan Sales, Trading

About MIAC Analytics

For over 30 years, Mortgage Industry Advisory Corporation (MIAC) has been the preferred provider of mortgage and asset-backed valuation and hedging software, MIAC Analytics™, MSR and whole loan brokerage services, secondary market risk management, and a complete CECL (Current Expected Credit Loss) solutions.

MIAC Analytics™ is the most sophisticated mortgage pricing and risk management software suite available. The MIAC Analytics™ suite includes VeriFi™, DR-Surveillance™, MIAC CORE™, and Vision™ to address FASB's new Current Expected Credit Loss (CECL) requirements with the industries best modeling practices. VeriFi™ is used to support and manage the data quality auditing and review process.

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