Modeling Mortgage Credit

Issues, Challenges and Thoughts on Future Models

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March 2009

What we have learned

A model can hurt a business just as much as it can benefit a business - if not more. Recently, many have come to understand this in a hard way.

Blindly relying on a model without questioning its validity or denigrating a model when it produces unsatisfactory results are two very common reactions. While these reactions are at the opposite extremes, they both come from the same misguided notion: that a model will/should *always* produce correct projections.

The collapse of the world financial market starting in 2007 has made virtually all financial models (many of which were working well at one point) obsolete. Naturally, this raises the question of whether these models are useful anymore. Perhaps what is more important for us is that we consider the following questions: What is the purpose of having a model? What are the issues and problems facing modelers in current practice? And, how can credit models help the financial industry once again?

To answer these questions, we have to understand what a credit model really does, what we should expect from a model and how to appropriately apply the model.

Mortgage Credit Models

Generally speaking, just like many other models, a mortgage credit model does two things:

1) Explanation of the past credit performance, and
2) Prediction of the future credit performance.
   For business applications, 2 is the ultimate purpose while 1 is to serve 2.

Mortgage credit performance is generally measured in these three aspects:

- Delinquency (Interruption of repayment)
- Default (Termination of a mortgage that is determined to be unrecoverable)
- Loss (Financial loss as a result of default)

While loss is the final measure of the financial consequence of a defaulted loan, delinquency and default have to be studied because of their impact on loss. Unlike mortgage prepayment, which is a single event, credit loss is the result of a process that consists of a series of events. Therefore, it takes multiple models to describe credit loss.

Like many other predictive models, mortgage credit modeling is driven by assumptions. In my opinion, the success of a model is all about making reasonable assumptions given that the model is correctly implemented. I view empirical data as the most important source for assumptions, and the data does not drive the models alone.

Empirical Data and Statistical Models

Before massive mortgage loan level data became available, credit models were built on risk factors gleaned from intuition and theories. A SDA (Standard Default Assumptions) curve is the simplest default model that is just a simple function against loan age. Another type of model is based on the same option theory that is widely used in equity trading. According to this theory, a borrower would choose to default his/her mortgage if it is under water – that is, the property value is less than the existing loan amount.

A more complicated model type is the structural model. A structural model tries to include all default risk factors and links them to a certain credit event (e.g. default) in a structured manner. The structure and the quantification of the impact of risk factors (sensitivity) are mostly based on expert knowledge and opinion. While the process of determining structure and sensitivity specification seems not very scientific, the structural model would always appear intuitive.

As credit score and credit bureau information were introduced to the mortgage industry in the mid 1990s, more and more loan level empirical data have also become available. The large volume of data on both loan characteristics and loan performance provides a basis for quantifying the impact of risk factors, the sensitivity, in a more scientific approach. It also leads to a widespread development of statistical models.

The overwhelming information flow made many believe that the business should operate using only empirical data, and statistical models developed based on empirical data should completely replace any expert opinions. Mortgage origination, risk management, financial forecast, government policymaking and audit practice have all embraced the notion that business decisions are only valid if they are based on empirical data and statistical models. This notion has evolved to be the mainstream business culture not just in the mortgage sector but almost the entire consumer banking industry over the past decade. This culture has not been seriously challenged until the market started a significant turn in late 2006.

A statistical model is a simplified summary of the past history, or past empirical data. A well-developed statistical model would explain the past performance well. However, it would be a big mistake to think that a good statistical model can always predict future performance as well. Many realize there is a leap of faith from a good interpretative model to a good predictive model, but few have questioned the wisdom of running a business based on pure statistical models.

The fundamental issue in statistics is to infer a population character/behavior from a sample that is a part of the population. The inference is meaningful only if the target population is stable relative to the sample. In mortgage research, we are dealing with a super population space that has a time dimension and extended dimensions of macroeconomic variables (e.g. interest rate, home price, etc.). Because of always-limited experiences in those dimensions, historical empirical data can only represent a subspace within the super space in which we are truly interested. Therefore, one can have access to the entire mortgage population data for a particular time period, but it still could be a biased sample of the super space. In this regard, any statistical model based on large data from a particular time period could be fundamentally biased when it is applied to a different time period.

Therefore, a statistical model would predict future mortgage performance well only if the future mortgage loans and the future market condition are very similar to the time where the empirical data is from. It is always the biggest assumption. However, once one employs a statistical model for decision-making, this assumption has already been implicitly made regardless if he/she is aware of it or not. When this assumption is seriously violated as it has been in the past two years, we have seen most models have failed almost completely. However, I view this to be more an "assumption" problem than a model problem.

Assumptions

Past empirical data, no matter how complete it is, represent a subspace in the super space that we have discussed. Attempting to predict the future is like navigating in this super space. The past empirical data point is no longer the interest of the business; rather, it serves as the starting point of the navigation journey.

As we move to unknown territories, assumptions become the key. From many years of modeling practice, I understand that making appropriate assumption is much more important than model fitting. The business "owners" (e.g. chief risk officers or portfolio managers) should ultimately be responsible for making the assumptions for these models.

There are two distinct types of assumptions: *model fitting* assumptions and *model running* assumptions. Model fitting assumptions mostly deal with data issues in empirical data – the original subspace. It is mostly a modeler's job. Model running assumptions, however, are the business owner's ultimate responsibility because they are the drivers of the business (and not the model). Model running assumptions have to be examined in a number of areas. For example, first let's say we make an assumption that the future unemployment rate rises above 12% (as an example). Given this assumption, what baseline default or loss rate would we assume if the unemployment rate goes above 12%? More importantly, would the model structure still be valid if the unemployment rate goes above 12%? For example, would the original LTV sensitivity measure still hold? If not, how the adjustments should be made?

Of course, there is little data for mortgage performance in a 12%+ unemployment-rate environment – the U.S. economy simply has not seen such an environment that often.

The answers to the above questions would have to be assumptions. These assumptions would tend to dominate the model results.

Coming up with more reasonable assumptions, therefore, is much more critical to a business than getting a better fit in a statistical model. It demands more focus, attention and effort, especially as we now navigate through uncharted waters.

Problems and Issues

Too much reliance on empirical data and statistical models in many cases has taken away human judgment and discouraged independent reasonableness thinking. Business problems are often special and challenging. Hoping a model that can solve all business problems is obviously very naïve.

The roots that cause many problems in the current modeling practice are 1) ignorance of the potential significant differences of today's market and tomorrow's market, and 2) the perception that the massive loan level data available to the industry contains complete information about the mortgage market.

Root 1) has made many only focus on the past data or the subspace, but have no sense of the super space or have no interest of going out of the subspace. Unfortunately, the world moves in the super space. Inexperienced statisticians or mathematicians have a tendency to be focused solely on the subspace they are working on. It is up to the business owners to review and come up with views of the super space.

The perception in Root 2) also has contributed to the data/model-only culture. The truth is, even within the subspace where massive past data is available *the information is still far from complete*. Loan-level data is vastly richer than aggregated pool level data, but it is still incomplete. We know that the absence of some key information could lead to biased estimates because the known information variables have to shoulder the impact of the unknown information. Also, the impact of different unknown information will be reflected in different baselines. It is also the reason that it is almost impossible to find a model that can fit the available data without introducing non-causal variables such as year, geographic location, specific loan originator, etc. The introduction of non-casual variables only helps produce better-looking curves. It does not explain well and it will not help predict. As long as information is incomplete, "one-model-fits-all" remains a modeler's dream. Over-fitting a model will not turn this dream into a reality.

There are other problems in model development and application. One problem is the disconnection between business and modelers. There are several reasons for this disconnection: 1) modelers do not have enough business knowledge and experience, 2) modelers tend to care more about academic soundness than business reasonableness, 3) modelers tend to think within the subspace that is the only area they can model, and 4) model validation protocols would discourage modelers from attempting to model the area outside of the available data. A typical example of such disconnection, for example, is the question of why the model won't run when home price falls 30% would meet with an answer like “because there was no such data in the past”. It sounds ridiculous but it is a fairly typical exchange that has been happening between business owners and modelers in real life.

Another problem is the disconnection between academic research and mortgage performance modeling work in the real business world. The mortgage performance problems are much more complicated than the problems that published models can handle, or no known modeling approach (e.g. survival model, competing risk model and multiple-choice model, etc.), can describe the mortgage performance very well. Part of the reason that the academic research is lagging in dealing with mortgage problems is because the massive mortgage data has never been made readily available to the academic world. Because of the nature of business competition, information and detailed research work have really never been shared among the business and academic worlds. The industry has to use simple and not well-developed techniques to model much more complicated problems.

Expecting a great proprietary model by simply hiring a couple of brilliant mathematics or statistics Ph.Ds without understanding the above big issues, learning how to check the results and getting involved in making assumptions is often fruitless if it does not actually hurt business at the end.

Thinking that developing models is just model fitting is problematic. Treating a statistical model as secret sauce in a black box is more than problematic.
Within the subspace that we think we know, there is no comfort zone. Information is not complete. The modeling technique is not well developed. A robust statistical model is not a sure thing as many tend to believe. Furthermore, the real purpose of the business is to deal with the super space. The challenges are just enormous.

The current model validation exercise presents another challenge to model development.

Model Validation

The empirical-data-and-statistical-model-only culture has influenced the practice of model validation. The validation practice, on the other hand, has also further reinforced the culture especially when the same approaches are taken by audit of government agencies.

Not surprisingly, like model development, model validation generally has only focused on the statistical modeling in subspace as well. It usually misses the more important question of how to make the model workable in the super space. The following are a few typical problems I see in the current validation practice:

1) <u>Overstating the importance of back-test.</u> Back-test is necessary. Treating the test as the most important piece of validation work is very questionable. The typical argument for this practice is a good predictive model should first be able to fit the past data well is flawed. This argument is based on the notion that there is a

'good' model that can work well in both the original subspace (past) and new territory (future). As discussed before, when the information, especially the key information, is unknown, it is very possible that the one-size-fits-all model (a true model) cannot be found. In this case a well-back-tested model would not work for the future market which is what we have recently seen. A good back-test would then only give a false sense of comfort, or for the prediction purpose, the back-test has not really validated anything useful. On the other hand, just as importantly, models being adjusted to work in a new environment might not pass the back-test. One extreme example would be the diminished impact of borrower's credit score for investment property, but registered as owner occupied in an unprecedented down housing market. The appropriate model adjustment for this example might not pass a typical back-test.

2) <u>Disconnection with modeling development.</u> Model development involves a lot of creativity. Many model auditors do not have production model development experiences. They often follow the procedures that are not quite up-to-date or not well prepared, and/or follow textbooks that are very much lagging in dealing with complicated problems like mortgages. It could easily turn into a bureaucratic process that is not really helping the model development, not to mention the business.
3) <u>Demanding a stable model.</u> Validation takes time, especially when the auditors are not very familiar with the subjects. In the fast changing world, models will have to be changed to keep the pace. It is not surprising to see models update faster than current validation can handle. While we cannot hold the world stable, the validation process will have to be adjusted.

The purpose of model validation is to eventually help model development. When the validation procedures are out of date or out of touch with business and the market, the model validation practice may hurt the model development and ultimately the business.

The changing world is not just a huge challenge to model development. It is just as huge a challenge to model validation.

Thoughts on Future Model System

As discussed above, applying a pure statistical model to business decision-making, especially in this market is very problematic if not disastrous. Future models will have to have a navigation function, the flexibility of handling various assumptions, and market interventions.

We propose a complete model system solution that is designed to work better in this volatile market. The model system would include the following components:

- Assumption generator
  The assumption generator will generate the assumptions in a more systematic and controlled way, and give the user the flexibility to input their own view.

- Repline, or subgroup, generator
  This will allow the user to make adjustment to particular replines (subgroups) based on their market knowledge. It is more important now as more loan modifications and other government interventions become more significant.

- Base model
  This model is a hybrid that combines a statistical model and a structural model. The model gives an initial baseline function and sensitivity specifications, which are estimated mainly from a statistical model. It will provide a base prediction if the market condition doesn't change much. However, the baseline function and sensitivity specification are flexible within certain structures so the users can make adjustments when they think it is necessary.

  It has always been a challenge to find a balance between granularity and simplicity when it comes to structuring a model. There is no clear cut answer. I would always argue for simpler structure over tighter fit.

- Performance monitoring system
  It provides the feedback of the model performance as the model helps to navigate through the uncharted territories. A good monitoring process can provide timely insight to business decision makers.

A complete model system is a much better approach to manage the risk to help make more timely and prudent decisions for the industry. It has been proven successful in helping businesses thrive in a volatile market.

It would be a more complicated system to develop and to maintain. It would also be more difficult to validate, and is necessary because the market and the economy is much more complicated than we think. We cannot expect the world to evolve according to our old experiences and protocols. Therefore, the purpose of model validation is not to make sure if models are developed according to the protocols. If a system can help people come up with reasonable views and make defendable decisions, it should be reflected in the validation protocols.

Final Remarks

A successful navigation needs to start from a reliable, firm and comfortable base. That is what a statistical model is for. While a good base is important, it does not move with us. Overstating the power of a base will not help navigation. As we have to move away from the base, one has to learn, to react, to survive and to succeed.

While a model cannot *always* predict correctly, it provides a benchmark, a base for learning, a systematic view and a source of guidance. There has never been any secret sauce. And there will never be a silver bullet. A good model will only be a necessary tool to help one navigate the changing world. No matter how good the tool is, the success is all in the driver's hands.