A NEW METRIC FOR HEDGING MORTGAGE PIPELINE FALLOUT RISK

How an Originator Can Reduce Overall Exposure to Interest Rate Risk

WHITE PAPER

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ABSTRACT

In this white paper, we introduce a new metric for hedging mortgage pipeline fallout risk. We benchmark that metric against common practice in the mortgage origination industry and show that by taking into consideration the steady-state nuances of a mortgage pipeline, a mortgage originator can reduce overall exposure to interest rate risk.

SECTION 1: INTRODUCTION

One of the primary components in establishing an appropriate hedge ratio is determining the likelihood that a locked loan will make it to funding/closing. For example, if a borrower is locked-in, but fails to meet credit worthiness verifications, then the lock will be cancelled, and the mortgage will fail to materialize. The scenario where a loan fails to reach funding is called fallout. The converse, where a loan successfully reaches funding, is referred to as pullthrough. If pull-through is not appropriately considered, then the hedge ratio will be too high, and the pipeline will be over-hedged.

In **FIGURE 1**, an example pipeline shock is shown. The net of the loans in the pipeline and the corresponding coverage (TBAs) demonstrates a balanced position whereby an interest rate movement in either direction will be nonbiased.

Conversely, in **FIGURE 2**, the value of the loans is adjusted by the loans' estimated pull-through likelihood. Without a corresponding adjustment in the hedge ratio, the net position is short, demonstrating an imbalanced exposure to interest rate changes. In order to mitigate potential imbalances, an accurate estimate of pullthrough is necessary.

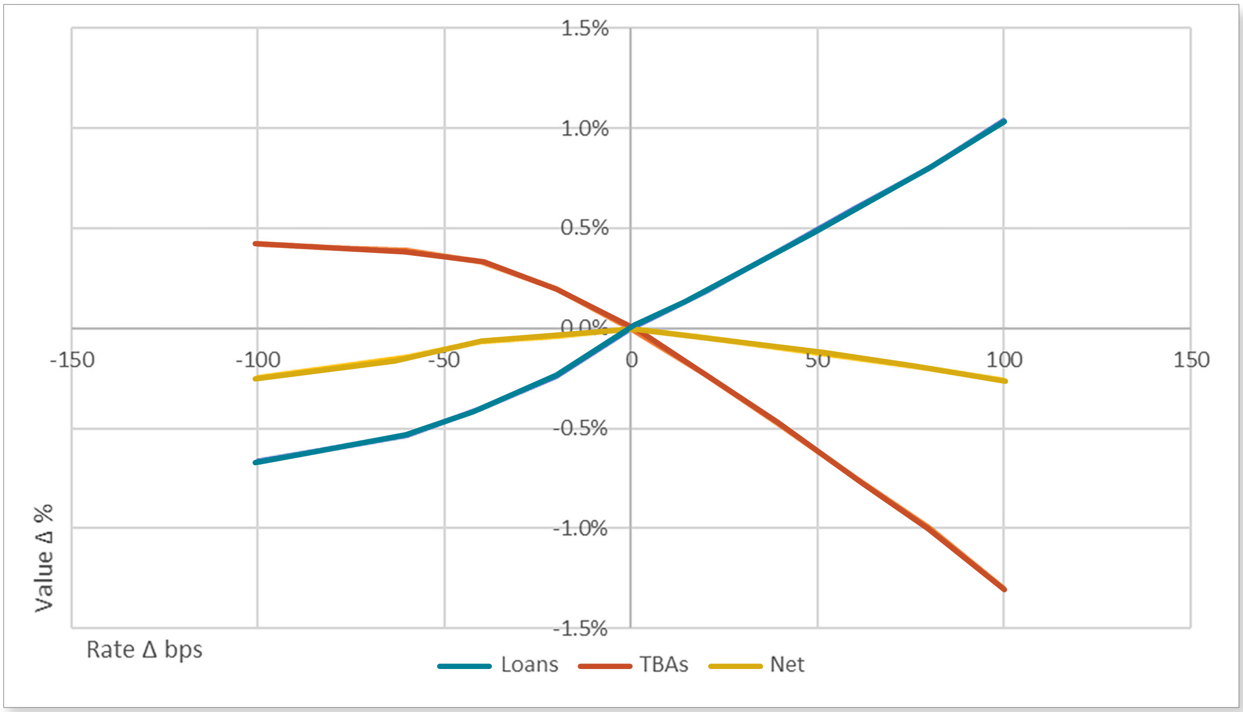

FIGURE 1

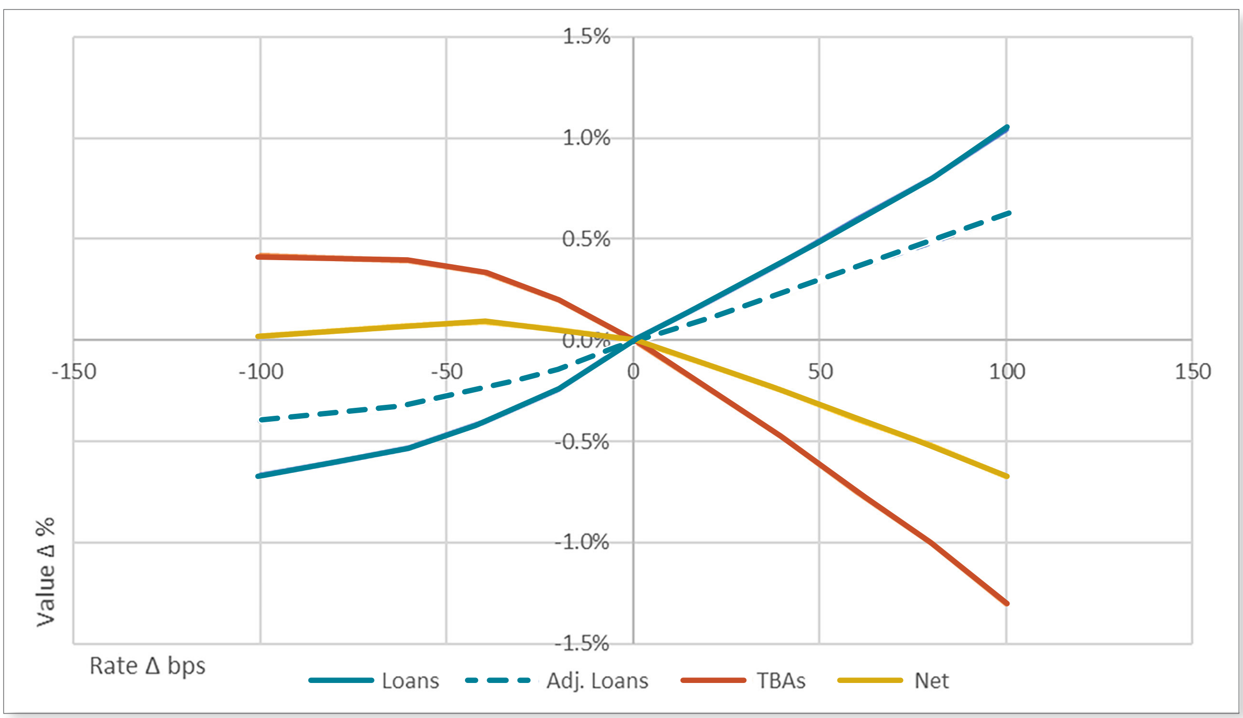

FIGURE 2

It is common for mortgage originators to calculate pull-through estimates by dividing the total number[1] of funded loans by the total number of locks [FORMULA 1]. This proportion is then used to adjust the hedge ratio accordingly. Sophisticated originators will attempt to stratify the data set into subsets (such as loan status) to attain more granular estimates [FORMULA 2].

FORMULA 1

$$PullThrough\% = \frac{Funded\ Count}{Locked\ Count}$$

FORMULA 2

Where i is a subset of the original data set:

$$PullThrough\%_i = \frac{Funded\ Count_i}{Locked\ Count_i}$$

Both calculations are flawed, because they fail to appropriately consider steady state dynamics within the mortgage pipeline. Specifically, they don't account for the fact that loans pull-through and fallout at different speeds.

During the origination process, the loan moves through many statuses as specified by the originator's internal operations. It is expected that the pull-through likelihood of the loan will increase as the loan moves towards later statuses. The lifecycle can be visualized as a state diagram, such as the one in FIGURE 3.

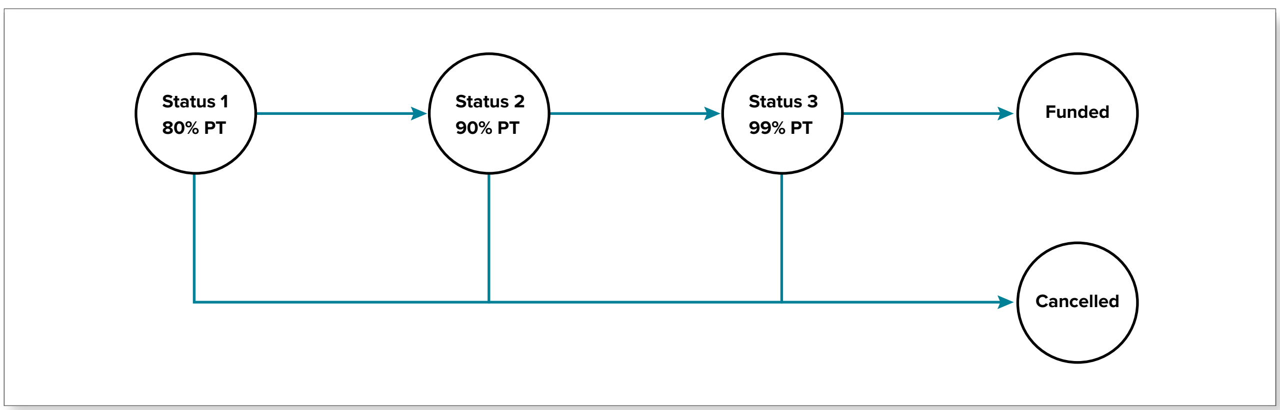

FIGURE 3

In general, loans that fund and loans that cancel tend to stay in the pipeline for different lengths of time. One can ascertain from FIGURE 3 why this would be the case. Loans have multiple paths to exit the pipeline to a "cancelled" state, but they will only have one path to exit the pipeline to a "funded" state.

[1] Historically, some pull-through methodologies have measured pull-through in terms of total volume. This approach is erroneous, because each loan represents a dependent binary variable (either the loan pulled through or it fell out). Weighting the dependent variables by loan amount will create an oversampling bias in the statistic towards larger loans. If loan amount is desired to be incorporated into the model, it should be incorporated as an independent (predictor) variable with its own prediction coefficient.

We measured the pipeline wait times for both funded and cancelled loans for a large national mortgage originator with a $300 million pipeline. As illustrated below in **FIGURE 4**, we see that for this originator, loans tend to fallout faster than they pull-through.

AVERAGE WAIT TIMES FOR A LARGE NATIONAL ORIGINATOR	
Cancelled Loans	Funded Loans
27.8	35.4

FIGURE 4

More specifically, the pull-through metric is the ratio of the arrival rate of funded loans, λ_{funded} to the total number of observations, $\lambda_{funded} + \lambda_{cancelled}$, where $\lambda_{cancelled}$ is the arrival rate of the cancelled loans [**FORMULA 3**].

When hedging, one does not hedge the arrival of a loan into the system. One hedges the loan for the entire lifecycle of loan as it exists within the system. For this reason, we must use Little's Law [**FORMULA 4**] to convert the λ into L, the steady-state length of the system.

By converting both λ_{fund} and λ_{cancel} into L_{fund} and L_{cancel} respectively, we can build a steady-state pull-through metric to establish a more accurate hedge ratio [**FORMULA 5**].

FORMULA 3

$$PullThrough\% = \frac{\lambda_{fund}}{\lambda_{fund} + \lambda_{cancel}}$$

FORMULA 4

$$L = \lambda W, \text{ where } W \text{ is the average wait time}$$

FORMULA 5

$$PullThrough\%_{steady} = \frac{L_{fund}}{L_{fund} + L_{cancel}}$$

Similar to prevailing convention, the data can be stratified, and the steady-state metric can be evaluated for each loan status [**FORMULA 6**].

FORMULA 6

Where i is a subset of the original data set:

$$PullThrough\%_{steady[i]} = \frac{L_{\text{fund}[i]}}{L_{\text{fund}[i]} + L_{\text{cancel}[i]}}$$

In section two, we continue this discussion by introducing our methodology for building an experiment to test the Little's Law concept. In section three, we show our results. In section four, we state our conclusions and discuss avenues for further research.

SECTION 2: IMPLEMENTATION

We constructed our experiment using walk-forward analysis [**FORMULA 3**]. Using the data set for a large national originator with a $300 million pipeline, we experimented over 365 days from the period of January 31st, 2016 to January 31st, 2017. For each day during the experimentation period, we gathered the preceding 365 days of loan information (loans that had either cancelled or funded) as a training set. Our testing set was the loans actively being hedged in the pipeline at the observation date.

For each observation date, we generated a model such as the one depicted in **FIGURE 5**.

STRATIFICATION	OBSERVATIONS	PULL THROUGH	W_{cl}	W_{ca}	PULL THROUGH $_{steady}$
BASE	8288	0.838	35.42	27.82	0.868
APPROVED [2]	6486	0.992	3.39	7.44	0.982
DOC PREP	4974	0.989	2.45	4.16	0.981
PROCESSING	4930	0.875	4.63	5.84	0.847
STARTED	3875	0.816	5.19	9.07	0.718

FIGURE 5

The model gives the pull-through estimates for both the non-steady-state and the steady-state metrics for both the base estimate and the decision tree estimates for each of the status stratifications. For every observation date, we would estimate each loan, n, in the testing set according to both its base value and its status stratification. We then identified whether each individual loan would eventually fall out or pull through.

[2] Note: Some statuses have been removed for brevity.

We calculated the various model performances by differencing each loan estimate (a ratio from 0 to 1) from the actual result. If the loan pulled through, the result would be 1. Conversely, if the loan was cancelled, the actual result would be 0.

We multiplied this difference by the loan amount to give us the dollar exposure that the estimate error caused to the hedge. By taking the absolute value of the sum of the individual loan exposures multiplied by the loan amount for each observation period, t, we determine the overall daily model performance owed to over- or under-hedging [**FORMULA 7**].

We then converted the exposure metric into a percent of the overall pipeline [**FORMULA 8**].

We used the median percent exposure value during the experimentation periodto gauge the overall efficacy of each strategy.

FORMULA 7

$$Exposure_t = \left| \sum_{n}^{N} [(\mathrm{Estimate}_n - \mathrm{Actual}_n) * \mathrm{LoanAmount}_n] \right|$$

FORMULA 8

$$PercentExposure_t = \frac{Exposure_t}{\sum_n^N LoanAmount_n}$$

SECTION 3: RESULTS

Loans within each status that will eventually cancel tend to stall, causing the steady-state pull-through metric to fall as opposed to rise. This disparity is more pronounced in the early stages of the loan lifecycle.

In **FIGURE 6**, we chart the average pull-through for actuals, baseline non-steadystate and steady-state estimates for the entire pipeline on each day during the experimentation. In **FIGURE 7**, we compare actuals to the stratified estimates.

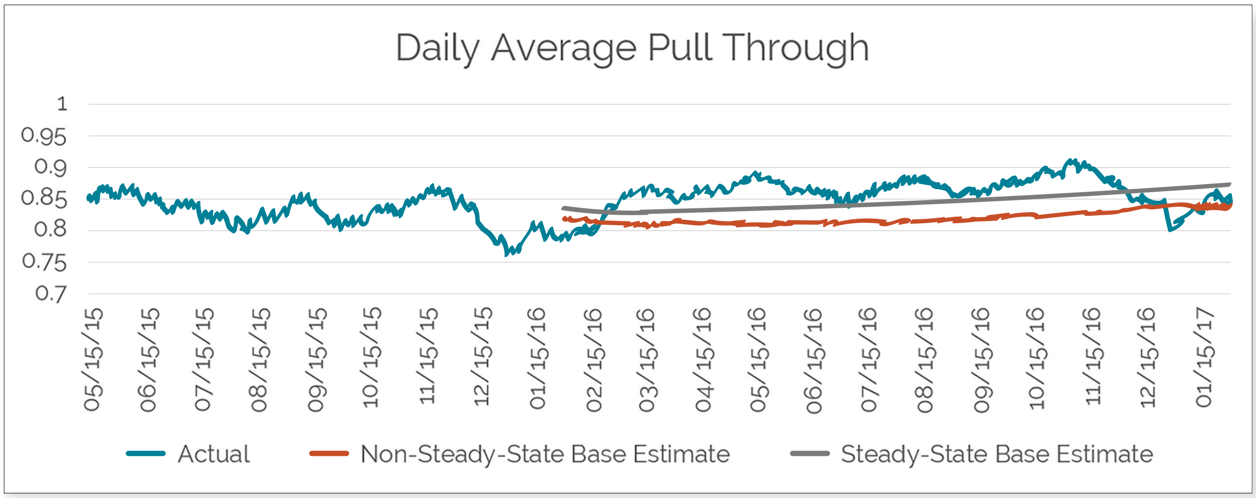

FIGURE 6

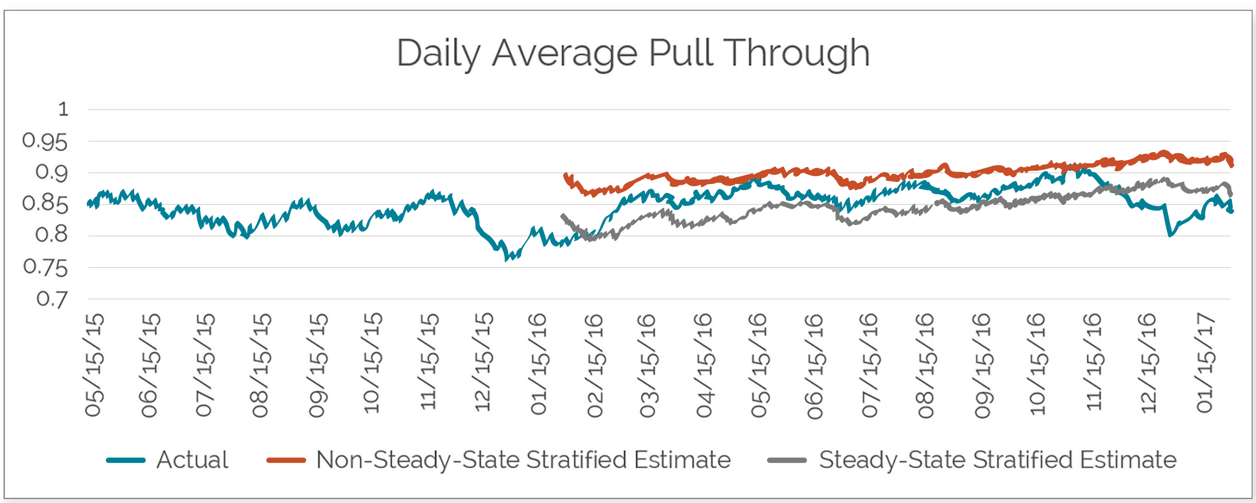

FIGURE 7

We note that for the base estimates, the non-steady-state metric tends to underestimate and for the stratified estimates, the non-steady state metric tends to over-estimate.

As shown in FIGURE 8, we discovered the median percent of the pipeline that was exposed due to pull-through estimation error for each strategy. The median percent-exposure illustrates that the steady-state metric outperforms the nonsteady-state metric in both the base and stratified estimation methodologies.

In addition to exposure, we also calculated the average dollar weighted estimate error for each of the strategies in FIGURE 9. The averages illustrate a bias in the non-steady-state metrics. The steady-state metrics are closer to zero, indicating the steady-state metrics are less prone to bias.

	MEDIAN PERCENT-EXPOSURE	
	NON-STEADY-STATE	STEADY-STATE
BASE	4.75%	3.19%
STRATIFIED	3.36%	2.83%

FIGURE 8

	DOLLAR WEIGHTED AVERAGE ESTIMATE ERROR	
	NON-STEADY-STATE	STEADY-STATE
BASE	4.23%	1.63%
STRATIFIED	-3.36%	1.66%

FIGURE 9

SECTION 4: CONCLUSION

We have introduced a new methodology for estimating pipeline fallout risk using Little's Law. Walk-forward analysis is used to show that (1) the standard convention for estimating pipeline fallout risk is biased, and (2) the new methodology outperforms the strategy employed by standard convention.

It is possible for the model to be elaborated upon using regression tree techniques, splitting the data where it is most appropriate to do so. For each node in the regression tree, the steady-state pull-through metric can be used to drive the calculations for entropy.

Lastly, we have avoided conversation on the impact of market movement on the pull-through estimations. It is reasonable to overlay a market movement model on top of the estimations described above.