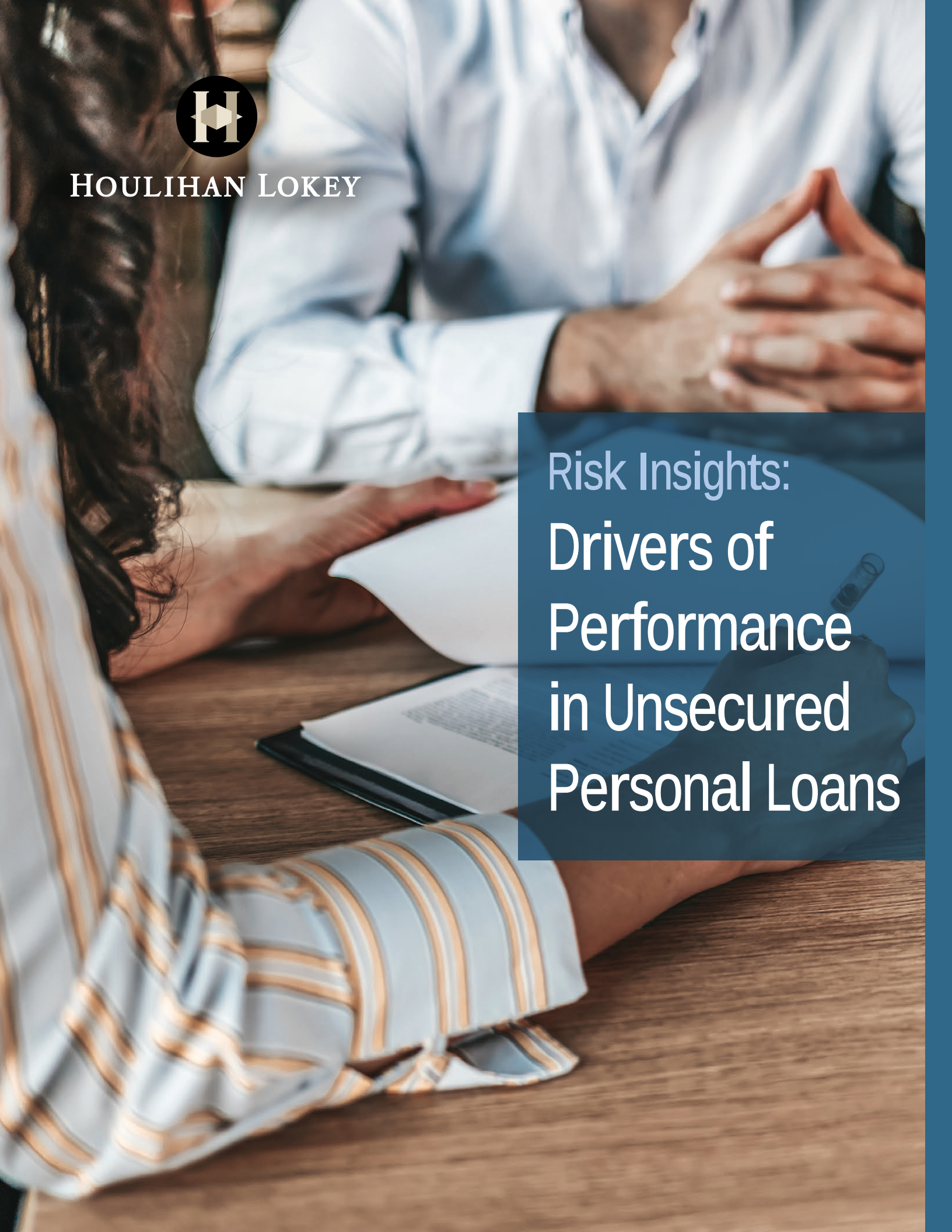

HOULIHAN LOKEY

Risk Insights:

Drivers of Performance in Unsecured Personal Loans

Drivers of Performance in Unsecured Personal Loans

With high coupon rates, unsecured personal loans can offer attractive returns to investors; however, investors also bear the risk of complete loss in the event of default. In our experience, the most successful investors have a deep understanding of the product and its nuances during underwriting. While platforms typically assign credit ratings when assessing the risk in the loans they originate, savvy investors go a step further and do their own research. In this article, we look into the key factors that affect risk and performance in this asset class, their relative contributions, and how they interplay with other important factors based on a study we have performed.

Analytical Framework

The analytical techniques used for this study are based on a parametric approach implemented via Houlihan Lokey's proprietary model (LAVA).

The dataset used in the study comprises the historical performance of LendingClub prime loans issued from Q2 2007 through Q4 2019,(1) covering approximately 35 million observations from 1.8 million loans.

Choice of Factors

The dataset contains a large number of attributes about loans, borrowers, and payments, representing factors with varying potential explanatory power. In addition to borrower attributes, certain exogenous factors (e.g., macroeconomic environment) are also believed to have a strong influence on performance. While some sophisticated investors use models based on hundreds of factors, we have limited our choice in this study to a handful of factors, primarily focusing on those that intuitively make economic sense and a couple that are not so obvious but could be potentially interesting. Given the nature of this study, we believe that our framework captures the essence without affecting its tractability. Our selected factors include the following:

Selected Factors	Performance Driver Category	Discussion	Observations From Dataset
1. Credit Score (FICO)	Borrower attributes that are easy to understand and have an intuitive effect on credit performance	A borrower with a higher credit score is expected to be lower risk	Range: 502 to 850 Average: 692
2. Debt-to-Income Ratio (DTI)		High DTI is likely indicative of greater risk	Range: 0.1% to 494% Average: 19%
3. Homeownership	Latent factors; less obvious but often discussed and potentially very interesting	Homeownership status of the borrower	Rent, Mortgage, Own, Other
4. Loan Purpose		The stated purpose of the loan	Debt Consolidation, Credit Card, Moving, Illness, Vacation, Wedding, Other
5. Unemployment Rate	Macroeconomic; not part of loan attributes but believed to have a strong influence	Rising unemployment is expected to increase loss expectations	Range: 3.5% (observed in Q4 2019) to 10% (Q4 2009) Average: 6.4%

(1) After Q1 2020, the data reflected changes in lending policy by the platform as well as unprecedented stimuli by the government in response to the COVID-19 pandemic. For purposes of this study, we have excluded that data.

Baseline Loan and Expected Loss

To illustrate our analysis, we selected a hypothetical newly originated loan (the Baseline Loan). For our selected factors, the attributes of this loan are assumed to be:

Loan Attribute	Assumption
Term	36 Months
Credit Score (FICO)	680
Debt-to-Income	20%
Homeownership	Mortgage
Purpose	Credit Card

The unemployment rate at the time of loan issuance is assumed to be 5% and assumed to remain at this level (we relax this assumption in a later section). We run this loan in LAVA assuming 90% loss severity, resulting in loss projection as shown below, which we will refer to as the "baseline loss expectation."

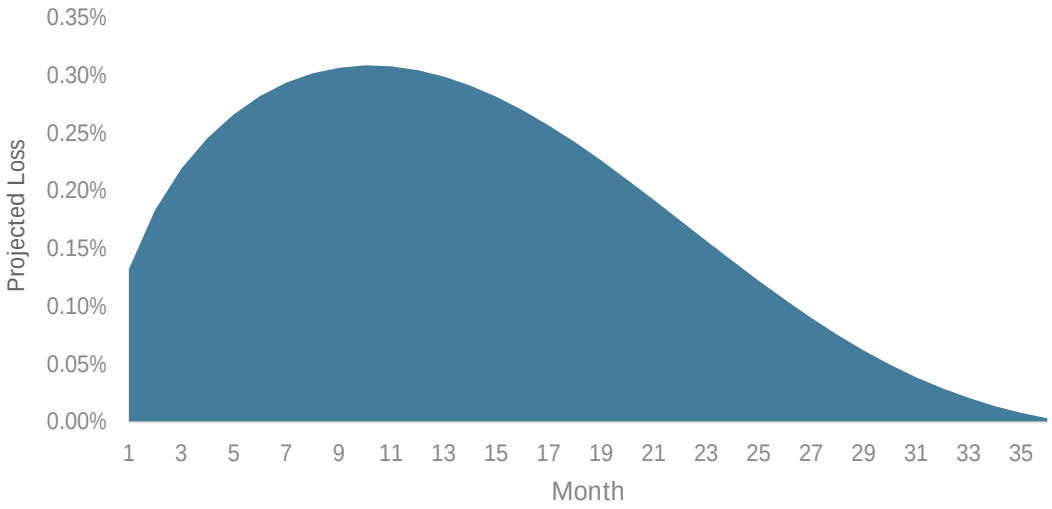

Figure 1: Baseline loss expectation.

In the following sections, we review the effect of each of our selected performance drivers individually.

Credit Score

Credit score is possibly the most commonly used metric to express creditworthiness of an individual. Due to its pervasiveness in consumer credit underwriting, we selected credit score as our first performance driver to explore. A low credit score indicates high credit risk and is generally associated with a greater expectation of loss, and the opposite is expected for a high credit score. However, to assess the effect of a credit score and its relative impact vis-à-vis other factors, a proper model is needed. Starting with the Baseline Loan, which has a FICO of 680, we stressed the credit score by +/- 100 points, which gives us three identical loans that differ only in their FICO scores. Running these loans in our model produces three different loss expectations, enabling us to study the effect of a credit score with greater detail.

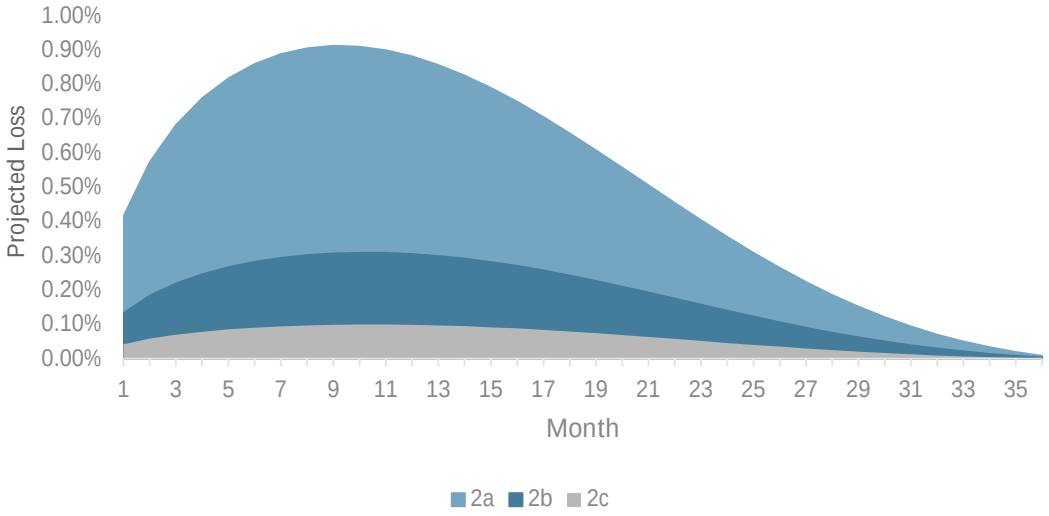

Figure 2: Effect of credit score.

	FICO	Total Projected Loss (as multiple of baseline loss expectation)
2a	580	2.8x
2b	680	1.0x
2c	780	0.3x

As expected, the credit score shows an inverse relationship with expected loss. Additionally, we find that the relationship is asymmetrical and nonlinear. A 100-point decrease in the credit score results in a much greater change compared with a 100-point increase.

Debt-to-Income (DTI)

DTI is another metric that lenders often use to assess creditworthiness. For our analysis, DTI is calculated as the ratio of a borrower's total monthly debt payments (excluding mortgage) divided by their monthly income. It represents a borrower's ability to service debt, and an elevated level is believed to indicate greater credit risk. To study the effect of DTI, we start with the Baseline Loan and change its borrower's DTI by +/- 10 points, which gives us three loans that differ only in their DTI. Running these loans in our model produces loss expectations that allow us to analyze the effect of DTI.

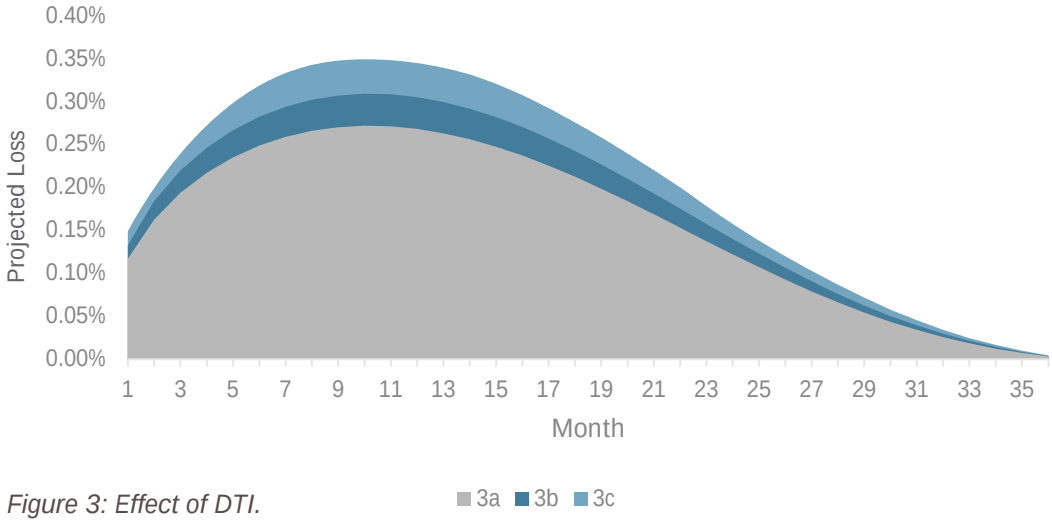

Figure 3: Effect of DTI.

	DTI	Total Projected Loss (as multiple of baseline loss expectation)
3a	10	0.9x
3b	20	1.0x
3c	30	1.1x

We find that higher DTI does in fact result in higher expected loss. Additionally, we note that the effect of DTI appears to be almost symmetrical; a 10-point increase in the DTI produces roughly similar absolute change as a 10-point decrease.

Homeownership

Is a borrower's homeownership status (sometimes referred to as "housing tenure") indicative of their creditworthiness? Is a homeowner a safer borrower compared to, say, a renter? We find out in this section.

Following the same approach as prior sections, we create three loans that differ only in their homeownership statuses, which are set to "None," "Mortgage," and "Rent." We then run these loans through our model, resulting in loss projections as shown below.

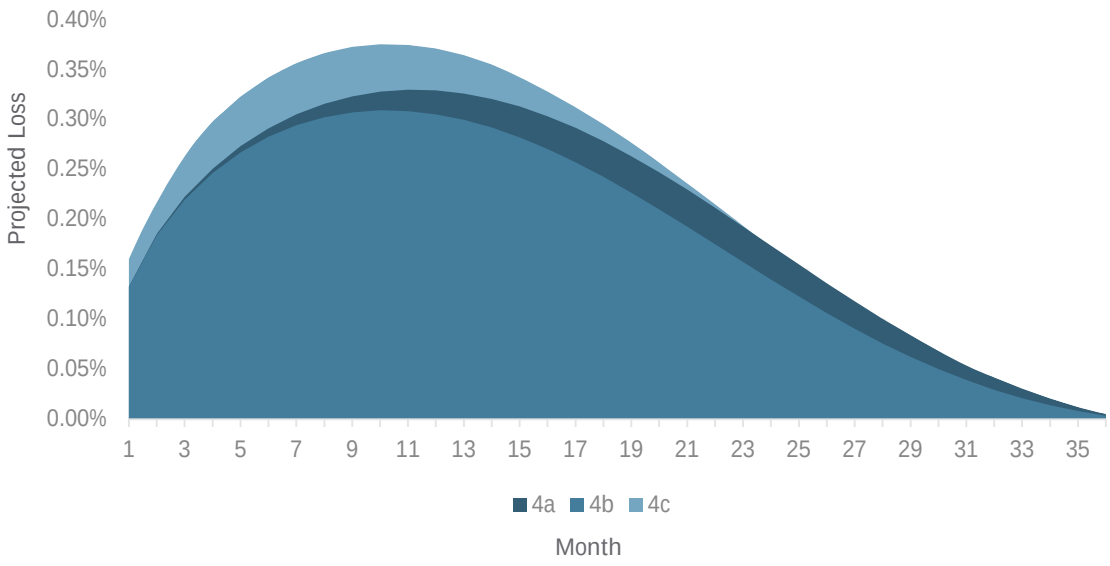

Figure 4: Effect of homeownership.

	Homeownership Status	Total Projected Loss (as multiple of baseline loss expectation)
4a	None	1.1x
4b	Mortgage	1.0x
4c	Rent	1.2x

We find that a loan to a mortgage-paying homeowner has a lower expected loss. Some prior studies have reported that homeowners tend to have much higher credit scores than renters,[2] so one might be tempted to conclude that the observed effect is obvious and expected. However, since the three loans being analyzed are identical in all aspects except for the borrowers' homeownership statuses, the effect of credit score (and other such factors) has already been isolated.[3] Therefore, the difference in expected loss (as seen above) is solely due to homeownership. A reasonable inference to draw might be that a mortgage-paying borrower is a more responsible user of credit in general.

Loan Purpose

When applying for a loan, the borrower typically states the purpose of the loan, indicating the intended use of funds. In this section, we explore whether the purpose of a loan has any effect on expected loss. Following the same approach as previous sections, we estimate expected loss under different assumptions of loan purpose. However, unlike the factors considered so far, we do not have *a priori* expectations about the effect of this factor and will be mostly relying on model output.

The projected losses for loans with different purposes were found to be as follows:

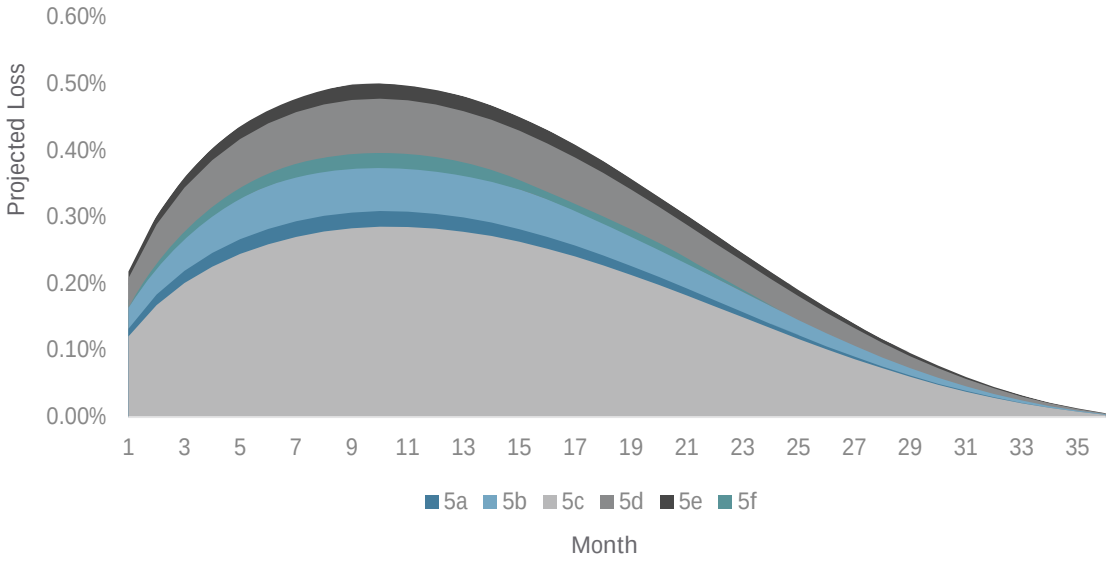

Figure 5: Effect of loan purpose.

	Loan Purpose	Total Projected Loss (as multiple of baseline loss expectation)
5a	Credit Card	1.0x
5b	Vacation	1.2x
5c	Wedding	0.9x
5d	Medical	1.5x
5e	Moving	1.6x
5f	Debt Consolidation	1.3x

(2) "Comparing Credit Profiles of American Renters and Owners," Housing Finance Policy Center, Li, Goodman, March 2006.
(3) If our selected factors excluded credit score, we think that the observed effect of homeownership would appear larger.

We find there is a fair bit of dispersion in expected loss, depending on the stated purpose of the loan. In particular, the loss expectation is lower for wedding loans and higher for moving or medical loans. Moving and medical situations involve uncertainty, which likely increases risk of repayment. On the other hand, when people get married, the household expenses may get shared, leading to better liquidity and overall improvement in credit quality. However, such reasoning (while plausible) is mere speculation. In absence of sufficient information to investigate such relationships, we do not delve further.

Macroeconomic Factors

Unemployment Rate

In addition to borrower attributes, the macroeconomic environment is also believed to be an important factor affecting the performance of unsecured loans. In particular, the unemployment rate is generally considered to be highly relevant. This factor represents the risk that the borrower loses their job and, along with it, the ability to repay the loan. Rather than the absolute level of unemployment, we think the change in unemployment rate from issuance to estimation date is more informative. Therefore, this is the subject of our focus in this section.

To set up the analysis, we consider two scenarios to describe the change in unemployment rate. At the origination date of loan, the unemployment rate is assumed to be 5%.

In the “Flat” scenario, the unemployment rate remains at 5%, i.e., unchanged from origination. This is also the base case to develop our analysis. In the “Up” scenario, it increases to 6% immediately after loan issuance. In the “Down” scenario, it falls to 4%.

The expected loss under the three scenarios is shown below.

The change in projected loss in the Up/Down scenarios versus base case was found to be about +/- 11% (as a percentage of baseline loss expectation).

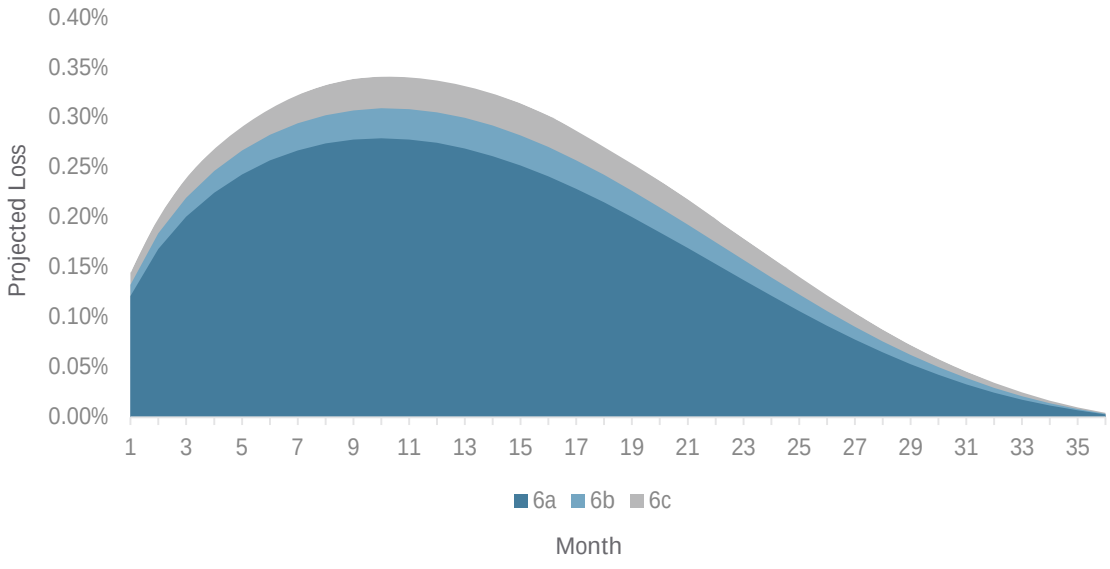

Figure 6: Effect of unemployment (for Baseline Loan).

	Unemployment Scenario	Total Projected Loss (as multiple of baseline loss expectation)
6a	Down	0.89x
6b	Flat	1.00x
6c	Up	1.11x

Next, we explore how results might vary if loan attributes were different (for instance, if the FICO was lower or higher). Recalling that a Baseline Loan has a FICO score of 680, we select two additional loans with FICO scores of 580 and 780. Running these loans in the same way as the Baseline Loan produced the following results:

Change in Projected Loss vs. Base Case

(% estimated off baseline loss expectation)

	FICO 580	FICO 680 (Baseline Loan)	FICO 780
Unemployment Down	-27%	-11%	-4%
Unemployment Up	+28%	+11%	+4%

This shows that a low FICO loan has greater sensitivity to unemployment scenarios. A possible explanation is that a high FICO borrower might have secondary income or additional means to repay the loan, whereas a low FICO borrower relies solely on income from employment. In any case, we can conclude that unemployment rate plays an important role in the performance of unsecured personal loans.

As seen in this article, the performance of unsecured personal loans can be affected by several factors. In addition to the factors examined in this study, other factors that may impact loan performance include the borrower's age and geographical location. Our team can help you make informed decisions as you think about:

- Stress testing and bespoke scenario analyses
- Independent review of underwriting criteria and flow agreements
- Portfolio optimization to maximize risk-adjusted returns
- Loss estimation including CECL

To learn more about our services and how we might be able to assist you, please contact the following team members:

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