Unemployment and the Consumer Credit Market

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Abstract

When a consumer borrows money to make a large purchase, his ability to pay down his loan is dependent on his likelihood to remain employed. Trends in the labor market provide valuable information regarding an employed person’s expected duration of employment as well as his expected duration of unemployment if he loses his job in the future. By understanding the relationship between the unemployment, separation, and job-finding rates, lenders can better predict the performance of their consumer loans. This paper models the potential effects of trends in the employment rate on loan performance and supports these results with empirical evidence from the used car industry.

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1. Introduction

Lenders in the consumer credit market continually search for any indicators that can predict their customers’ ability to pay down their loans. They evaluate personal finances, employment, and even residence histories before they agree to the terms of a loan. The rationale behind their evaluations is simple; people who have good credit history, a solid job, and stable living conditions are more likely to make all of their payments. A lender’s profitability is mostly determined by his ability to accurately analyze these signals and lend only to those candidates who are the most credit worthy. A potential buyer is required to provide lenders with information that acts as a signal demonstrating his ability to pay.

Understandably, some of the more valuable indicators of payment performance are the borrower’s current income and job security. Lenders usually cap the size of their loans in such a way that the monthly payments are lower than a specified fraction of the consumer’s monthly income. People with no income usually do not receive any financing. Employment is the single most important signal that lenders use to evaluate credit worthiness.

As the aggregate unemployment rate fluctuates, the information contained in a consumer’s employment signal may fluctuate as well. Employment during a deep recession may correspond to entirely different loan performance than employment during an economic boom. For example, if unemployment is very high, this may signal that the economy is in a recession. If during a recession people are more likely to be fired, then the signal of employment is not as meaningful to lenders, since the consumer is more likely to lose his job in the near future. In this case lenders would prefer to tighten their
credit standards when unemployment is high in order to minimize their exposure to higher firing rates during a recession.

But there is also another effect that may push performance in the opposite direction. It is a reasonable assumption that individuals have different innate probabilities of being laid off. Some people may be rarely fired due to personal qualities that are unobservable to the lender, such as dedication or loyalty towards their employer. If unemployment is very high, the composition of those who are employed will be more heavily weighted towards the dedicated type of worker since other less dedicated workers have already been fired. Those who do have jobs during a recession may be more likely to keep their job for longer because they are more likely to be the type of worker who is rarely laid off.

If this composition effect overshadows the first case, lenders should conceivably lower credit standards when unemployment is high. The signal of employment is stronger when unemployment is high since the composition of the employed labor force consists of more reliable workers who will tend to pay off their loans better than those who are employed in a good economy.

Of course, this is not the entire story. If a consumer receives a loan and then is fired before paying down the premium, he may not immediately default at the time he is fired. He may have enough savings to continue making payments until he finds another job. A borrower’s ability to pay off a loan to term is therefore also a function of how quickly he can find a job if he is ever fired.

The findings of this paper indicate that a borrower’s future ability to find a job once fired is the most significant relationship between employment trends and loan
performance. Variations in the rate at which unemployed workers can find jobs, called the job-finding rate, appear to have the most effect on a borrower’s likelihood to pay down his loan.

2. Employment and Loan Performance Theory

Unemployment, a stock, can be decomposed into the different flow rates as workers shift in and out of employment. Changes in the unemployment rate are determined by both the rate at which people are fired, called the separation rate, and the rate at which people are hired, the job-finding rate. The flow of workers in and out of the labor force also affects the unemployment rate, but these rates are smaller in magnitude and not as relevant to the consumer credit market.

By analyzing the separation rate, lenders can make an approximation of how likely one of their customers is to lose his job before he finishes paying down the loan. Once an employed customer receives a loan, the most natural expression of his likelihood to lose his job while still in debt is his employment hazard function. This is the probability that he will lose his job during a given month conditional on being employed continually from the start of the loan up to the month previous. An increase in the aggregate separation rate would correspond to a comparable increase in the set of aggregate employment hazard functions.

Although closely related, there is one crucial difference between the separation rate and the employment hazard rate. The separation rate is the percentage of employed workers that leave employment, while the employment hazard rate is the percentage of
workers that leave employment and have been continuously employed since a specific date, corresponding to the month of origination.

Lenders are most interested in this expected employment hazard rate of their customers because they can then estimate what percentage of their loan portfolio will default over time. Since the separation rate is the proportion of workers who lose their job every month, the expected future separation can be used to estimate the employment hazard function of a borrower. Obviously lenders would prefer to loan to workers who have lower employment hazard functions, so any insight into the expected future separation rate is valuable information.

Similarly, expected job-finding rates can be used to estimate how easily laid-off borrowers can find new employment. Lenders would prefer to loan money in situations when the expected job-finding rate is high, since a subsequent lay off would be less likely to result in a default. If new jobs are hard to find, then a borrower who has just lost his job will have trouble finding a new source of income and is more likely to default on his loan.

2.1 The Composition Effect

As mentioned in the introduction, different unemployment levels may correspond to different compositions of the employed labor force. As the composition of the employed pool varies, the expected employment hazard rates of those employed also change simply because different types of workers are more likely to be laid off than others. The driving factor behind this effect is an inhomogeneous labor force where workers have different innate separation rates.
Consider a model which tracks the employment probabilities of a pool of workers that are employed at a given time \( t=0 \), corresponding to the month when borrowers must verify employment just before originating a loan. The model imposes a simplistic measure of labor force homogeneity that categorizes each worker in the labor force as either a ‘good’ type or a ‘bad’ type. Let \( p \) be the proportion of the labor force that, when employed, is fired each month at a rate of \( a_t \) where \( t \) is the amount of time since origination. Let \( 1 - p \) be the proportion of the labor force that is always employed. Define \( h(t, u) \) as the hazard function at time \( t \) given unemployment rate \( u \) at time \( t = 0 \), the probability of a worker being laid off at time \( t \) given that he has been employed since \( t = 0 \), conditional on \( u \). For example, \( h(1, u) \) is equal to the proportion of the employed labor force that is ‘bad’ multiplied by \( a_1 \).

\[
h(1, u) = \frac{(p - u)}{1 - u} \times a_1
\]

We can see how the hazard rate varies with time by explicitly calculating \( h(t, u) \):

\[
h(t, u) = \frac{P(\text{Survives until } t-1 \& \text{ fired at } t \mid u)}{P(\text{Survives until } t-1 \mid u)} = \frac{E[(p - u)a_i \prod_{i=1}^{i=t-1} (1 - a_i) \mid u]}{1 - p + E[(p - u)\prod_{i=1}^{i=t-1} (1 - a_i) \mid u]}
\]

If we assume that \( a_i \) is independent of \( u \), then

\[
h(t, u) = \frac{(p - u)C(t)E[a_i]}{1 - p + (p - u)C(t)}, \quad q(t) = E[\prod_{i=1}^{i=t-1} (1 - a_i)]
\]

where \( q(t) \) is the expected probability that a ‘bad’ worker remains employed from \( t = 0 \) until \( t = 1 \). \( q(t) \) is decreasing in \( t \) and between 0 and 1.

This of course is a strong assumption. An employed ‘bad’ individual’s probability of being laid off from month to month may be correlated with unemployment due to
business cycles or other general trends over time. However, by assuming independence, it is possible to pinpoint the exact effect of the composition effect. If $E[a_t]$ is independent of $t$, a reasonable assumption, then $h(t,u)$ is decreasing in both $t$ and $u$.

The hazard function decreasing in $u$ agrees with the intuition outlined earlier that given higher unemployment the composition of the employed is more weighted towards workers who have innately lower hazard functions (‘good’ workers). Similarly, as time progresses, the pool of workers who were employed at $t=0$ shift more and more towards ‘good’ workers since those with higher hazard functions are more likely to be fired and drop out of the pool.

Notice that if the labor force becomes homogenous, then $u$ drops from the equations and hazard rate is no longer directly dependent on the initial unemployment rate. If $p = 1$, then the hazard function simplifies to $E[a_t]$. If $p = 0$, then by definition the hazard rate is also zero. Therefore the composition effect of unemployment of the hazard rate is driven by the degree of homogeneity of the labor force.

The significance of this model is also limited by the magnitude of variance in the unemployment rate. Even over the course of several years, unemployment rarely moves
more than a few percentage points. If unemployment rate moves from 3 to 5 percent, a relatively large jump, the pool of employed workers shrinks by only slightly more than 2 percent. Unless this 2 or 3 percent of employed workers is strikingly different than everyone else, it is unlikely that such a small percentage change would result in a noticeable composition shift in the overall employed labor force.

On the other hand, if this 2 or 3 percent of workers that move from employment to unemployment is concentrated in a specific subpopulation, then a lender whose customers fall into this subpopulation might see a pronounced change in the type of their customers who are employed. Instead of changing the composition of the entire employed labor force evenly, changes in unemployment would effect only the composition of part of the labor force.

For example, workers from households with total income less than $3,000 a month are more likely to be unemployed than those from households with total income greater than $3,000, since workers with lower incomes tend to have jobs that are less stable. Therefore, changes in unemployment will effect the composition of the low income employed labor force more than the high income labor force.

People who belong to the lower income class are less likely to be able to purchase consumer goods without borrowing since they on average have lower savings. Most customers who receive financing from industries such as used-car dealerships, furniture stores, and jewelry retailers come from households with lower incomes for this reason. The lenders in these industries therefore loan money to a subset of the labor force that is most strongly affected by changes in the composition of the employed labor force.
2.2 The Separation Rate and Recessions

Facing a recession, a lender might instinctively tighten his credit rating standards and decrease the amount of money he loans. One possible explanation is that as the economy weakens and unemployment rises, more people will lose their jobs over the next few months, decreasing their ability to pay down their loans. This idea implies that high unemployment rates correspond to high separation rates.

Only recently have labor economists concluded that the separation rate is nearly constant or even counter-cyclical, and at least does not rise during a recession. According to Robert Hall’s most recent paper on the components of unemployment, the conventional wisdom that more people are fired during a recession was false during the most recent recession of 2000, and appears to be false for earlier recessions as well. Variations in unemployment are instead due to the job-finding rate, which is historically more unstable and cyclical than the separation rate. Since separation rates do not rise during recessions, it is incorrect to associate a weak economy and high unemployment with high separation rates (Hall, 2005).
Clearly, the graphs of Employment to out of Labor Force and Employment to Unemployment are nearly constant. The graph of Employment to New Jobs seems to slight drop of the period, but this component of the separation rate is not relevant to loan performance since these workers remain employed.

Lenders therefore should not restrict business solely based on a fear of high separation rates during a recession. In fact the implications are even stronger; since the separation rate is close to constant, the proportion of employed workers that will lose their jobs in the future is almost perfectly predictable. The expected performance of a portfolio of loans should be unaffected by the separation rate.

2.3 The Job-Finding Rate

Given that the separation rate is nearly constant, large variations in the unemployment rate must be due to trends in the job-finding rate. In a weak economy, a drop in the job-finding rate will cause the unemployment rate to rise. Since recessions may last for a number of years, initially high unemployment will suggest that the job-
finding rates will be lower in the immediate future. Unlike the separation rate, the job-finding rate is extremely volatile and tends to cyclically move in one direction for several years (Hall, 2005).

![Calculated Job-finding Rate](image)

This graph, using data calculated in Hall (2005), clearly shows that the job-finding rate follows strong trends over time and that each consecutive rate is closely correlated with the rate of the previous month. This cyclical volatility is crucial to the relationship between unemployment and loan performance.

Since all borrowers must be employed before receiving a loan, the job-finding rate is relevant to loan performance only after a borrower loses his job. If a borrower does lose his job, he will probably default on his loan after a couple of months unless he can find another source of income. Many borrowers, especially those with lower incomes, do not have substantial savings. If this is the case, those who are fired will only have a few months to find another job before defaulting on their loan. The monthly job-finding rate becomes crucial to lenders, since finding a second job is the only reliable way for borrowers to continue making payments.
The effect of the job-finding rate on loan performance will be more pronounced with employees in industries associated with low monthly incomes and unstable jobs. The durations of employment are shorter for people in these industries compared to those in other industries. Workers in lower income brackets may be fired and hired several times a year. As these people try to pay down a three year loan, their ability to pay will be determined by their ability to quickly find a new job after being laid off.

The relationship between the unemployment rate and the job-finding rate is subtle. Unemployment is a stock variable while the job-finding rate is a flow variable. Using the current unemployment rate as a predictor of current and future job-finding rates is tricky. Depending on the direction of the economy, initial low unemployment may correspond to the start of a recession and future job-finding rates that will decrease over time. Put differently, if the job-finding rate continues to fall over an extended period of time, unemployment should rise at an increasingly faster pace. Over this period, higher unemployment would be correlated with lower future job-finding rates. An analogous situation would be if the job-finding rate were to continuously grow as unemployment drops. In this case, lower unemployment would be correlated with higher future job-finding rates, essentially the same relationship.

However, this relationship would be reversed in a different economy. If unemployment is rising due to a low job-finding rate, but the job-finding rate itself is rising over time, then higher unemployment would correspond to higher future job-finding rates. The same relationship would apply if the job-finding rate is high but decreasing over time. This correlation could last for an extended period of time if the change in the job-finding rate over time is small enough.
This complex set of cases can be roughly approximated with a simple mathematical relationship. Assuming that the net flow into the labor force is zero, a constant rate of unemployment will correspond to a constant ‘steady state’ job-finding rate, since the separation rate is nearly always constant. If the job-finding rate were to fall slightly from its steady state level, then the unemployment rate would rise linearly for a period of time. It is easy to see that this relationship gets extremely complex as the sizes of both the employment and unemployment pools change, but the first order approximation is very useful:

\[
\frac{du}{dt} = F_0 - F
\]

where \( F_0 \) is the steady state job finding rate.

It is clear from this equation that if \( F \) is smaller than \( F_0 \) and decreasing over time, then \( u \) is increasing at a growing pace. Likewise, if \( F \) is greater than \( F_0 \) and increasing over time, then \( u \) is decreasing at a growing pace as well. This would correspond to the starting period of a recession or economic boom where high unemployment is coupled with low job-finding rates.

On the other hand, if \( F \) is smaller than \( F_0 \) and increasing or larger than \( F_0 \) and decreasing, then the economy is correcting. The correlation between unemployment and the job-finding rate would then be reversed. For the precise relationship between the unemployment, separation, and job-finding rates that does not require a linear approximation, see Robert Shimer’s “Reassessing the Ins and Outs of Unemployment” (2005).
3. Description of Data

The data used to estimate loan performance comes from a used car auto financing company. They currently operate 79 dealerships in 11 states. In 2003 they sold over 50,000 cars. Their business is fully integrated. They get their cars from government auctions, repossessions, and trade-ins, and do all the financing themselves. They out-source repossessions, but all other aspects of the business are done within the company and are coordinated at the company’s corporate headquarters.

They specialize in financing people with low income and bad credit. Since January 2001, the median household income of their customers is $2,392 per month. Their median annual interest rate, or APR, is 28.7%. The legal maximum in the United States is 30%. Of their loans whose term has already expired, more than 55% defaulted before being paid down. To compensate for the high risk of loaning to low income individuals with no credit, this company charges high APR’s, marks up the sales price, and requires a down payment. The average term length is 42.3 months, the average monthly payment is $402, and the average sales price is $11,249.

The nature of this company makes it a perfect subject for studying the relationship between unemployment and loan performances. Since the majority of their customers work in low income, unstable jobs, they represent the segment of society that shift in and out of unemployment most frequently. Unemployment trends that affect the aggregate consumer credit market are magnified in this sector of the labor force.

Second, unlike the rest of the used car industry which is dominated by individually owned dealerships, this company uses standardized pricing and credit rating techniques. Sales prices are determined at the corporate headquarters, not by store
managers. Starting in 2001, the company introduced its own credit rating system which followed a specific formula based on income, credit history, type of residence, etc. All of this standardization means that location managers make very few decisions. Every dealership is selling the same set of product for the same prices. Data from each individual sale can therefore be analyzed on a national, company-wide level instead of by individual dealership.

The data given to me by this company contains a record for every car sold since January 1999. Each record contains, among other data, the origination month, sales price, down payment, APR, monthly payment, term of the loan, the company’s credit grade of the customer (after 2001), and default month if applicable.

The unemployment data used in the analysis section is the unemployment rate by city published by Bureau of Labor Statistics. The data is not seasonally adjusted since seasonal changes in the unemployment and job-finding rates are just as significant as market changes in affecting the composition and hazard rates of the labor force. The unemployment rate corresponding to each loan is the unemployment rate in the city of the dealership at the month of origination.

4. Survival Analysis

The best method to analyze this company’s loan performance is survival or duration analysis. Each loan corresponds to an observation that begins when the loan is originated and ends when the loan defaults or reaches the end of its term. Loans that are still active, such as loans originated last year that have not yet defaulted, are considered
censored observations and only provide information for the first portion of the lifetime of the loan.

The driving function behind survival analysis of a pool of loans is the hazard function. The hazard function is the most intuitive measure of loan performance because it gives the risk of default at every moment during the loan’s lifetime. For example, a loan that has a constant hazard function has the same probability of defaulting each month no matter how old it is. While a pool of these loans would decay exponentially, the likelihood of an active loan defaulting is the same every month.

Below are graphs of the aggregate hazard function and survival function of all loans originated from May 2002 through October 2003 with term lengths from 39 to 42 months, sorted by credit grade:
The hazard function graphs clearly pinpoint the difference between credit grades. Higher credit grades correspond to lower hazard rates and higher survival rates. More importantly, the difference appears to be proportional. The shapes of the hazard functions are all similar; different grades simply seem to alter the hazard rate by a ratio that is fixed over time. This is a convenient property of hazard functions. Any variable that affects loan performance equally over a loan’s lifetime, such as credit grade, will only modify the magnitude of the hazard function and not affect its shape.

For this reason, the best statistical model for measuring the relationship between unemployment and loan performance is a proportional hazard model, or Cox regression. The regression model estimates a baseline hazard function and then varies this baseline function proportionally based on the independent variables. The functional form of the model is

\[ h(t \mid x) = \exp(B \cdot x)h_0(t) \]

where \( x \) is the vector of the covariates, \( B \) is the vector of the regression coefficients, and \( h_0(t) \) denotes the baseline hazard function. The regressions in this paper report the hazard
ratio for each variable, which is equal to \( \exp(B_i) \). Intuitively, the hazard ratio is the proportion by which the baseline hazard function is either increased or decreased corresponding to a one unit change in the independent variable.

Listed below are the number of observations and summary statistics for all variables used for the regressions in the following sections. The data corresponds to all loans originated during the 18 month period from May 2002 through October 2003 that have term lengths from 39 to 42 months.

<table>
<thead>
<tr>
<th>Observations by Credit Grade</th>
<th>Frequency</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>A+</td>
<td>3,337</td>
<td>6.59</td>
</tr>
<tr>
<td>A</td>
<td>4,312</td>
<td>8.41</td>
</tr>
<tr>
<td>B</td>
<td>10,468</td>
<td>20.42</td>
</tr>
<tr>
<td>C</td>
<td>13,772</td>
<td>26.86</td>
</tr>
<tr>
<td>C-</td>
<td>10,539</td>
<td>20.56</td>
</tr>
<tr>
<td>D+</td>
<td>4,856</td>
<td>9.47</td>
</tr>
<tr>
<td>D</td>
<td>2,609</td>
<td>5.09</td>
</tr>
<tr>
<td>D-</td>
<td>1,333</td>
<td>2.60</td>
</tr>
<tr>
<td>Total</td>
<td>51,266</td>
<td>100</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Variable Name</th>
<th>Mean</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Down Payment</td>
<td>$714</td>
<td>$544</td>
</tr>
<tr>
<td>Monthly Payment</td>
<td>$396</td>
<td>$49</td>
</tr>
<tr>
<td>Origination Unemployment Rate</td>
<td>6.26%</td>
<td>1.58%</td>
</tr>
<tr>
<td>Absolute Change in Unemployment One Year after Origination</td>
<td>-0.523%</td>
<td>0.640%</td>
</tr>
</tbody>
</table>

### 4.1 Origination Model

The following is a Cox regression of survival time with unemployment, credit grade, city, down payment, and monthly payment as independent variables. The most important aspect of this regression is that all the independent variables are known to the lender at the time of origination. The goal of this model is to determine which variables
affect the expected hazard rate of a loan. Any additional information that is revealed after
the origination of the loan, such as the unemployment rate any time after the month of
origination, can not affect the expected hazard rate of the loan at the time of origination,
and therefore is not be included in the regression.

The set of observations are all loans originated during the 18 month period from
May 2002 through October 2003 that have term lengths from 39 to 42 months. Loans
originated before May 2002 and after October 2004 are omitted because of changes in
company-wide credit grading policies, rapid expansion in sales, and shorter durations of
observed lifetimes.

Survival Time vs. Unemployment at the Month of Origination

The following table shows the results of a Cox regression analysis using the Breslow method for ties. The survival variable, Loan Survival Time, represents the time in months that a loan lasts before it either defaults or is censored. In this model, if a loan reaches the end

<table>
<thead>
<tr>
<th>Loan Survival Time</th>
<th>Hazard Ratio</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Origination Unemployment Rate</td>
<td>1.046</td>
<td>.0173</td>
</tr>
<tr>
<td>Down Payment</td>
<td>.9998</td>
<td>.000015</td>
</tr>
<tr>
<td>Monthly Payment</td>
<td>1.0017</td>
<td>.00016</td>
</tr>
<tr>
<td>A+</td>
<td>.816</td>
<td>.0433</td>
</tr>
<tr>
<td>B</td>
<td>1.281</td>
<td>.0470</td>
</tr>
<tr>
<td>C</td>
<td>1.784</td>
<td>.0619</td>
</tr>
<tr>
<td>C-</td>
<td>2.143</td>
<td>.0761</td>
</tr>
<tr>
<td>D+</td>
<td>2.410</td>
<td>.1235</td>
</tr>
<tr>
<td>D</td>
<td>2.450</td>
<td>.0937</td>
</tr>
<tr>
<td>D-</td>
<td>2.511</td>
<td>.1063</td>
</tr>
</tbody>
</table>

Grade A used as default, dummy variables for City of Origination are not shown. All coefficients are significant at the 1% level.
of its term, it is considered censored at that point. Intuitively, this is because loan performance is not observed after the loan is paid down. In this sense, all future months are ‘censored’. This simplification is consistent as long as all observations have similar term lengths.

The relevant variable is the Origination Unemployment Rate, in units of percentage points. It corresponds to the unemployment rate in the city where the sale occurs during the month of origination. Down Payment, Monthly Payment, Credit Grade and City of Origination are all control variables.

The hazard ratio for the unemployment rate is 1.046. The interpretation is that a one percentage point higher unemployment rate during origination corresponds to a hazard ratio that is approximately 1.046 times bigger each month. For example, a loan that is originated when the unemployment rate is 5% is 1.046 times more likely to default every month than a loan that is originated when the unemployment is at 4%.

Below are two graphs that outline this effect. They are the estimated hazard and survivor functions for Cox regression models, corresponding to unemployment levels of 4, 6, and 8 percent. The other covariates of the baseline function are defined at a down payment of 600, monthly payment of 400, credit grade B, in the city of Albuquerque.
A more practical representation of these results would show how the covariates actually affect the expected value in dollars of a loan. The estimated hazard function can be used to determine the effects of the covariates on the expected payoff of a specific loan. This is done by recovering the survival function associated with estimated hazard function. The survival function is related to the cumulative hazard function:

\[ s(t \mid x) = \exp\left(-\int_0^t h(s \mid x)ds\right) \]
The expect value of a loan, labeled \( V(x) \), is the sum of the expected value of each month’s payments discounted according to the company’s time value of money. This can be approximated by integrating the discounted survival function and multiplying by the size of the monthly payment:

\[
V(x) = m \int_0^T \exp(-rt) \cdot s(t \mid x) \, dt
\]

where \( m \) is the size of the monthly payment, \( T \) is the length of the term in months, and \( r \) is the discount rate.

Take the following example, calculated using numerical methods in STATA. Using the estimated hazard function for a 40 month loan with down payment of 600, monthly payment of 400, credit grade B, in the city of Albuquerque, and origination unemployment rate of 4%, at a discount rate equal to the companies average cost of capitol of 6%, the expected value of the loan is $9,785. At an origination unemployment rate of 5%, the expected value of an otherwise identical loan drops to $9,671. Similar calculations could be made for loans with different characteristics.

To understand why high unemployment is associated with low loan performance during these months, it is necessary to view this model not as a regression of the performance of independent loans but as a regression of a time series of loans. This means that each subsequent month of loans is affected by a similar long term history of unemployment, offset by only one month. For example, while a loan originated in May 2003 will have a different unemployment rate at origination than a loan originated in June, they are both affected by nearly identical employment trends since they are only separated by one month.
Consider the graphs of the unemployment rates in the six cities where this company sold the most cars during the 18 month period, corresponding to 75% of all their business. Smaller cities are omitted from this graph to avoid clutter. Any bias due to city size is insignificant since all cities had similar trends and these graphs are only used as qualitative tools to help explain the regression models. The vertical lines represent the first and last months of origination during the period.

At the first month of origination the unemployment rate tends to be roughly constant, or in some case slightly increasing. The unemployment rates appear to peak during the middle of 2002, in accordance with the nation-wide recession which started in 2000. Over the next 18 months of originations, the unemployment rate tends to fall. The rate of decline seems to slowly increase after the last pool of originations in October 2003. Using change in unemployment as the first order approximation of the job-finding
rate, it appears that the job-finding rate is generally increasing during the lifetime of the loans, most significantly for the loans originated towards the end of the 18 month period. Therefore, during this period, the high unemployment seems to correspond to lower future job-finding rates, since the first origination pools are further from the high job-finding rates in 2003 and 2004.

This relationship provides the most plausible explanation for the negative correlation between the performance of a loan and the unemployment rate at month of origination. During the 18 month period, high unemployment is associated with low future job-finding rates and visa versa. Lower job-finding rates correspond to more defaults and therefore worse performance.

To verify this finding, future change in the unemployment rate is regressed on the unemployment rate at the month of origination. This OLS single-variable regression measures the correlation between the unemployment rate and the change in the unemployment rate over the following year, in each relevant city during the 18 month period.

\[(u_{i,t+12} - u_{i,t}) = B(u_{i,t})\]

where \(i\) is an index for each city.

<table>
<thead>
<tr>
<th>Change in Unemployment vs. Unemployment at Origination</th>
</tr>
</thead>
<tbody>
<tr>
<td>OLS regression</td>
</tr>
<tr>
<td>n = 738 (18 observations corresponding to each month in the 41 relevant cities or metropolitan areas)</td>
</tr>
<tr>
<td>Change in Unemployment</td>
</tr>
<tr>
<td>------------------------</td>
</tr>
<tr>
<td>Origination Unemployment</td>
</tr>
<tr>
<td>Constant</td>
</tr>
</tbody>
</table>
Clearly the unemployment rate, measured in percentage points, is closely correlated with the change in the unemployment rate, also measured in percentage points. Since changes in the unemployment rate and the job-finding rate move in opposite directions, high unemployment corresponds to lower future job-finding rates. This correlation is what drives the relationship between the origination unemployment rate and loan performance.

It is also worth noting that a linear approximation of the job-finding rate is a conservative estimate of the actual job-finding rate. As the unemployment rate drops, the size of the pool of unemployed workers decreases. Therefore, in order to maintain even a constant rate of unemployment decline, the job-finding rate must increase simply because there are a smaller number of workers who are looking for a job every month. This implies that the growth in the job-finding rate over the relevant period of time is more significant than the approximation would suggest.

Finally, the first survival regression does not provide any evidence to support the composition of the labor force model discussed in chapter 2.1. The composition model predicted that given high unemployment, the pool of employed workers will be comprised of more reliable workers since other less reliable workers are unemployed. This would result in a positive correlation between performance and the unemployment rate, the opposite of the actual findings. The shifts in composition are overshadowed by the effects of changes in the job-finding rate.

This is probably due to a combination of two factors. First, the composition of this customer base is relatively homogenous since every customer within a specified credit grade fits within a narrow range of characteristics from monthly income to marital status.
Since the company is able to observe and control for so many factors, there may only be a few unobserved factors that can contribute to heterogeneity in the employment hazard rates. Second, the jobs held by most of the customers are temporary so the job-finding rate is crucial in providing an alternate source of income once a borrower becomes unemployed.

4.2 Job-Finding Model

The job-finding rate by definition affects loan performance due to trends that happen after the month of origination. Since all borrowers are employed at the start of the loan, the job finding rate does not become relevant until they lose their job sometime in the future. While trends in the job-finding rate are correlated with the unemployment rate during the month of origination, the actual driving factor is changes in the job-finding rate that occur after the month of origination.

Even though the unemployment rate at origination is known at the time of the sale, its ability to predict performance is limited because it is not directly the driving factor behind the model. The unemployment rate is simply correlated with the driving factor, the job-finding rate. Since this correlation can change as climate of the economy changes, the model’s goal of predicting performance is only satisfied within a specific local set of conditions.

The following regression uses the exact same pool of loans and the exact same control variables as before, except performance is regressed on change in the unemployment rate over the first year of the loan instead of the unemployment rate at the month of origination. Change in unemployment in the first year is used as a proportional
approximation of the aggregate annual job-finding rate. While this regression does not have the same possibility of prediction as a regression where all covariates are known at the month of origination, change in the unemployment rate over the first year of the loan is a much more direct estimate of the job-finding rate than the unemployment rate at the month of origination.

Once again, the set of observations are all loans originated during the 18 month period from May 2002 through October 2003 that have term lengths from 39 to 42 months:

Survival Time vs. Change in Unemployment over the First Year of the Loan

Cox regression -- Breslow method for ties
No. of subjects = 49113 Number of obs = 49113
No. of failures = 17807
Time at risk = 680887
LR chi2(47) = 2191.94
Log likelihood = -183640.67 Prob > chi2 = 0.0000

<table>
<thead>
<tr>
<th>Survival Time</th>
<th>Hazard Ratio</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Change in Unemployment</td>
<td>1.05</td>
<td>.0170</td>
</tr>
<tr>
<td>Cash Down</td>
<td>.9998</td>
<td>.000015</td>
</tr>
<tr>
<td>Monthly Payment</td>
<td>1.0017</td>
<td>.00016</td>
</tr>
</tbody>
</table>

Dummy variables for Credit Grade and City of Origination are not shown
All coefficients are significant at the 1% level

The relevant variable is the change in the unemployment rate over the first year of the loan, or equivalently the unemployment rate one year after origination minus the unemployment rate at origination. Its units are percentage points. It corresponds to the change in the unemployment rate in the city where the sale occurs.

The hazard ratio for the change in the unemployment rate is 1.051. The interpretation is that a one percentage point higher unemployment rate during origination
corresponds to a hazard ratio that is approximately 1.051 times bigger each month. The intuition is the same as before. Higher changes in unemployment represent lower job-finding rates, which decrease performance.

The z statistic for the change in unemployment (3.07) is slightly greater than the z statistic for unemployment in the first survival regression (2.70), which suggests that change in unemployment is a slightly better indicator of performance. This is expected since change in unemployment is a more reliable estimator of the job-finding rate. However, given that the data in both regressions are time series, it is impossible to completely prove that the change in the unemployment rate is a more significant covariate than the origination unemployment rate. If performance is regressed on both origination unemployment and change in unemployment with the same set of data and all the same controls, the results are still relatively inconclusive.

Survival Time vs. Origination Unemployment and Change in Unemployment

Cox regression -- Breslow method for ties
No. of subjects = 49113  Number of obs = 49113
No. of failures = 17807
Time at risk = 680887
LR chi2(48) = 2203.19
Log likelihood = -183635.04  Prob > chi2 = 0.0000

<table>
<thead>
<tr>
<th>Survival Time</th>
<th>Hazard Ratio</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Origination Unemployment</td>
<td>1.058</td>
<td>.0179</td>
</tr>
<tr>
<td>Change in Unemployment</td>
<td>1.062</td>
<td>.0174</td>
</tr>
<tr>
<td>Control variables for Down Payment, Monthly Payment, Credit Grade and City of Origination are not shown</td>
<td></td>
<td></td>
</tr>
<tr>
<td>All coefficients are significant at the 1% level</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
The z statistic is only slightly greater for the change in unemployment (3.66) than it is for the unemployment at origination (3.36). As observed earlier, over the 18 month period, unemployment and the following change in unemployment are so closely correlated that their effects cannot be separated. Many more years of data from different economic climates are needed to completely resolve this question.

5. Conclusion

For the observed set of loans, it appears that loan performance is dictated by trends in the job-finding rate that occur after the loan is originated. The positive correlation between performance and changes in the unemployment rate during the lifetime of the loan indicates that performance is linked to uncertainty in the aggregate economy. The task of predicting the performance of a loan as it is originated is therefore a complicated process. Since the job-finding rate can move cyclically in one direction for an extended period of time, past unemployment and job-finding rate histories can be carefully used to estimate future job-finding rates. If economists are able to formulate an accurate model for variations in the job-finding rate, lenders could theoretically improve their ability to estimate the expected performance of their loan portfolios.

The findings of this paper could be greatly improved and refined with more accurate labor data. If job-finding rates calculated by city were available, it would no longer be necessary to use the change in the unemployment rate as an approximation. Also, using statistics that focus only on the relevant consumer classes instead of the entire population would strengthen the significance of any conclusion. With more years of data through different economic climates coupled with population-specific data, perhaps the
effects of changes in composition could be observed. All of these considerations should be taken into account so that the relationship between the labor market and the consumer credit market can be better understood.

References


