Credit Performance: Does Situational Data like the Economy Matter?

Robert B. Avery
Paul S. Calem
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The views expressed are those of the authors and do not necessarily represent those of the Board of Governors of the Federal Reserve System or its staff.
“Our [the industry] credit-scoring models are based on credit histories that reflect only prosperity...loans that were approved during the period of economic expansion may now be affected by changed circumstances.”

--Fed Governor Olsen, 5/21/02
What are the Implications of this Point?

- Credit Performance is situational and depends on economic environment.
- Credit History—and credit scores—since they are cumulations of performance should also depend on past economic environment.
- Logic can be extended from national business cycle to regional or local economy.
- Could also be extended to individual “exogenous” situational factors such as layoffs, health problems or divorce.
Research Question

- Examine the relationship between economic environment and both credit performance and assessment of credit history

- Use detailed “account-level” data for 250,000 nationally representative people selected from national CB in June of 1999
Preview of Conclusions

• Find some evidence that economic conditions matter suggesting that scores of individuals in economically depressed areas may be inappropriately low.

• Also find some serious limitations in the nature of the data reported to the CBs that effects ability to use situational data in scores.
Background– CB files

- CB data come in four forms: public records, inquiries, trade line, and collection accounts. Each “account” is a separate record.
- Focus here on trade lines (e.g. mortgages, credit cards). For each account we have:
  - Date opened, “closed,” and last reported
  - Amount currently owed, past due, credit line, maximum amount owed
  - Current payment status, 48 month history of payments
  - Type of lender and account, various comment codes, and account ownership
Background – CB files

• CB files are like FBI raw files. Purpose is to provide input to analysis not do the analysis
• Judgemental underwriting or a “custom” or application score can be based on other information outside CB. A Bureau or classic “FICO” score based only on CB data.
• CB data appear to be extraordinarily clean with virtually no “validity-type” errors.
• Problems appear to relate more to missing data or accounts which are inconsistently reported
Background – CB files

• Problems seem to arise in following accounts which are transferred, closed, or sold to a collection agency

• Some of these problems are significant and effect the ability of analyst to use situational factors in developing a scoring model

• At the very least problems require assumptions to deal with missing data
Background – CB files

• 35% of trade line files are not currently reported and not reported as closed
  – 13% of these are missing current balance
  – 30% of these are missing current payment status (though 5/6 of these have 0 balance)
  – 2.5% of these show current payment status of a minor delinquency with a positive balance. These represent 57% of all accounts which are “currently” minor delinquent
  – Many of these are closed-end accounts past date due
  – Appears accounts often are not closed when they are transferred, paid off or sent to collection
Background – CB files

- Particularly acute problem with mortgages. 80% or individuals with 2 or more open mortgages showed that one mortgage was opened within 2 months of the last reporting of the other mortgage for approximately the same amount. Often one account is listed as past due. Hard to distinguish between sale of servicing and a new loan.
Background – CB files

- Big problem with major derogatories. Hard to follow accounts when sent to collection department or agency. Cannot tell if one or two accounts. Sporadic reporting of chargeoffs and payoffs.
- Looked at all individuals who took out a new mortgage in first 6 months of 1999. About 5% showed a major derogatory. About ½ of these showed that the account was unpaid. This appears to be an inaccurate representation as new mortgagees are typically required to pay off seriously delinquent accounts.
Background – CB files

• Collection agency accounts also a problem.
  – 30 percent of individuals show some collection account.
  – 88% are small (under $500).
  – Source of creditor not coded. We parsed name of creditor to estimate type. Estimate 52% are medical; 24% are utilities; only 5% are for normal “trade line-type” loans (some of these are double counted).
  – Payoff information sparse and often not linked to the original account. Inconsistency in reporting multiple small charges or single consolidated amount.
Background – CB files

- Credit limit missing in 34 percent of open revolving accounts currently reported

- Account ownership status missing for many non-primary account holders. Cannot tell if authorized user, cosigner, or co-applicant
Implications for Scoring

• Any differential based on the timing of a major derogatory hard to do
• Number of accounts and current minor delinquencies and unpaid collections likely overstated
• Need to estimate credit limit for those missing it
• Hard to differentiate behavior on single and joint accounts (useful for divorce) or accounts opened since a specific date (complicated by transfers which appear to be new)
• Model builders must address these and other problems
Modeling Framework

• Given difficulties in using situational variables it is important to see if there is value in it
• First test is to use economic environment—economic conditions in the borrower’s county—during times when credit history (and credit performance) is measured and see relationship to performance
• Crude tests only approximating analysis that would be done in full development of a score
Modeling Framework

• Traditional scoring model: \( y_{it} = F(Y_{it}, \eta_{it}) \)
  
  o \( y_{it} \) = period \( t \) repayment performance of individual \( i \) on representative account (perhaps of particular type)
  
  o \( Y_{it} \) = vector of measures of credit usage and repayment performance by individual \( i \) prior to period \( t \)
  
  o \( Y_{it} \) may include, for example, *number of accounts 30-120 days delinquent (currently and in past two years)*; *number of accounts ever charged off or in collection*; *number of accounts of different types*; *number of new credit accounts opened in past year*; *credit line and revolving account utilization rates*
Modeling Framework

• Our hypothesis: \( y_{it} = f(X_{it}, C_i, \mu_{it}) \)
  
  o \( X_{it} = \) vector of exogenous factors affecting borrower \( i \)'s ability to pay (local economic conditions, personal trigger events, etc.)

  o \( C_i = \) measures of borrower’s willingness to make timely payments (measures of reliability, character, financial responsibility, etc.)

  o Obstacles to empirical estimation: unobserved borrower attributes; limited information on timing and context of delinquency episodes; serial correlation of economic conditions.
Modeling Framework

• We estimate: \( y_{it} = F(y_{i,t-1}, x_{it}, x_{it-1}, Z_i, \phi_{it}) \)
  
  o Period \( t \) (“performance period”) is 7/97 – 6/99 and period \( t-1 \) (“credit evaluation period”) is 7/95-6/97.
  
  o \( y_{it} \) tracks performance on new accounts opened on or after 7/97 but no later than 3/99
  
  o \( y_{it} = 1 \) if account becomes at least 60-days delinquent during the performance period, and 0 otherwise.
Modeling Framework

• We estimate: \( y_{it} = F(y_{i,t-1}, x_{it}, x_{it-1}, Z_i, \phi_{it}) \)
  
  o \( y_{it-1} \) measures maximum delinquency during the evaluation period on any account open as of 7/95
  
  o \( y_{it-1} =0 \) if no delinquencies; =1 if 30 days; =2 if 60 days; =3 if 90-150 days; =4 if collection (extended version)
  
  o \( x_{i,t-n} \) = measures of local economic conditions:
  
  o \( Z_i = \) control variables: Age of the borrower; seasoning of the loan; Census division; Census tract relative median income; Census tract minority percentage
Modeling Framework

- $x_{i,t}$: 1998 county unemployment rate; 1997-1998 MSA or state house price appreciation rate; 1997-1998 percent change in county per-capita income

- If “situation” matters, period $t$ economic environment will be reflected in payment performance
Modeling Framework

- $x_{i,t-1}$: 1994 to 1997 change in unemployment rate

- If “situation” matters, past performance may overstate or understate current credit risk depending on past context.
Modeling Framework

• Clearly, we face the data limitations already noted for scoring models

• Also limited to data from relatively homogeneous economic environment (broad-based expansion)

• Still, we believe we can test whether “situation” matters and whether there may be value added in attempting to control for it
Empirical Procedure

• OLS estimation (General Linear Model)

• Close to 200,000 observations

• Weighting for single vs. joint accounts
## Results

### Means of variables

<table>
<thead>
<tr>
<th>Category</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>% with no prior delinquency</td>
<td>75.2</td>
</tr>
<tr>
<td>% with prior 30-day</td>
<td>16.1</td>
</tr>
<tr>
<td>% with Prior 60-day</td>
<td>4.5</td>
</tr>
<tr>
<td>% with prior 90-120 day</td>
<td>4.5</td>
</tr>
<tr>
<td>% in low/moderate income ZIP</td>
<td>13.7</td>
</tr>
<tr>
<td>% in (95%) non-minority ZIP</td>
<td>52.8</td>
</tr>
<tr>
<td>1998 county % unemployed</td>
<td>4.20</td>
</tr>
<tr>
<td>1998 house price % change</td>
<td>5.57</td>
</tr>
<tr>
<td>1998 % change per capita income</td>
<td>5.57</td>
</tr>
<tr>
<td>Change in unemployment 1994-97</td>
<td>-1.22</td>
</tr>
</tbody>
</table>
Results

\[ y_{it} = F(y_{i,t-1}, x_{it}, x_{it-1}, Z_i, \phi_{it}) \]

Mean of dependent variable: 0.021
Intercept 0.070 (18.68)
No prior delinquency (base 90 day) -0.062 (38.4)
Prior 30-day (base 90 day) -0.047 (26.8)
Prior 60-day (base 90 day) -0.028 (12.7)
Low/moderate income ZIP 0.014 (12.5)
Predominantly non-minority -0.023 (12.8)
1998 county % unemployed 0.0008 (4.23)
1998 house price % change -0.0007 (3.16)
Change in unemployment 1994-97 -0.0013 (3.19)
Extensions

• Incorporate past charge-offs, collections

• Borrower-level analysis

• Sample segmented by age-group (over- and under-50)

• Sample segmented by revolving vs. installment credit
Conclusions

• “Situation” matters
  o Value added to considering current economic environment
  o Value added to considering past context
Conclusions

- There are limitations to what can be accomplished with available data
  - Ideally, credit reporting systems would collect more data on timing of delinquency, collection processes, situational factors