BANK FOR INTERNATIONAL SETTLEMENTS

BIS Working Papers

No 146

Consumer credit scoring: do situational circumstances matter?

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January 2004

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Abstract

Although credit history scoring offers benefits to lenders and borrowers, failure to consider situational circumstances raises important statistical issues that may affect the ability of scoring systems to accurately quantify an individual's credit risk. Evidence from a national sample of credit reporting agency records suggests that failure to consider measures of local economic circumstances and individual trigger events when developing credit history scores can diminish the potential effectiveness of such models. There are practical difficulties, however, associated with developing scoring models that incorporate situational data, arising largely because of inherent limitations of the credit reporting agency databases used to build scoring models. .

JEL Code: G2
Keywords: Credit scoring, Consumer credit, Credit risk.

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Copies of publications are available from:

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Press & Communications
CH-4002 Basel, Switzerland

E-mail: publications@bis.org

Fax: +41 61 280 9100 and +41 61 280 8100

This publication is available on the BIS website (www.bis.org).

ISSN 1020-0959 (print)

ISSN 1682-7678 (online)

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Introduction[1]

Over the past 20 years, US consumer credit markets have become increasingly national in scope and characterised by intense competition. This trend has been facilitated by the development of low-cost, statistically derived credit scoring models used to mechanically screen, price and monitor consumer credit accounts. Although such models have been used in consumer lending for some time, their role has expanded in recent years because of improvements in the coverage and accuracy of data maintained by consumer reporting agencies (sometimes referred to as credit bureaus), which are at the heart of most credit scoring models. Indeed, many credit scoring models, particularly those used for screening unsecured open-ended consumer credit such as credit cards, are now based entirely on information contained in credit reporting agency files. These models, known as credit history scoring models, have been proven to be highly predictive of future loan performance. They generally involve significant fixed costs to develop, but can be used to screen additional consumers at very low marginal costs, enabling institutions to compete for customers in a national market.

Credit history scoring models offer the advantages of low-cost and consistent quick screening, and because such models are based only on information contained in credit reporting agency files, they can be used to screen almost any potential customer. However, because they are based on less information than that traditionally used in consumer credit screening, they have the potential drawback of being less accurate than models based on a fuller set of information. In particular, situational information about the economic or personal circumstances of individuals is generally not accounted for in credit history scoring models. That is, these models typically are constructed without any interactions between the information in consumer credit records and information pertaining to the economic environment in which the consumers live or work, or other contextual information about their personal circumstances. Thus, an individual who has experienced credit problems for transitory reasons, such as a local economic recession or a personal adverse trigger event such as a medical emergency, typically would be assigned a comparable score to an individual whose credit problems reflect chronic excessive spending or an unwillingness to repay debts. The outlook for future performance on new or existing credit for these two individuals, other factors held constant, may be quite different.

In this paper we examine the potential costs of failing to incorporate situational data into consumer credit evaluations. We also discuss practical difficulties associated with the development of credit scoring models that incorporate situational data. These difficulties arise in large measure because of inherent limitations of the credit reporting agency databases used to build many scoring models. These issues have potential importance for public policy. They touch on the questions of whether the trend towards a national consumer credit market is likely to be associated with higher consumer credit losses and whether the legal rules regarding information collected by the credit reporting agencies might inadvertently be contributing to a less accurate credit risk screening system.

For our analysis, we rely on a sample of credit files from a national credit reporting agency obtained by the Board of Governors of the Federal Reserve System (see Avery et al (2003)). These data contain the credit records of a large, nationally representative cross section of individuals. The information obtained is similar to the "raw" data that would be available to a credit history model builder when constructing a credit history score. The credit reporting agency also supplied the contemporaneous credit score for each individual based on the company's own proprietary credit history scoring model.

We perform three indirect inferential tests of the potential value of situational information in credit scoring. The first test addresses the potential relevance of local economic conditions in forecasting future credit performance. Specifically, we examine whether, holding constant an individual's credit history score, there is additional predictive information in his or her local economic circumstances. If so, it would imply that a credit history score formed without taking account of local economic conditions will underpredict the future credit performance of an individual who has gone through a temporary period of adverse local economic conditions (performance will be better than expected).

[1] Part of the work of this study was done while the first author, Robert Avery, was on leave at the BIS. The views expressed are those of the authors and do not necessarily represent those of the Board of Governors or its staff. We wish to thank Raphael Bostic, Frank Diebold and seminar participants at the BIS, Freddie Mac and the Federal Reserve Bank of Philadelphia for helpful comments and suggestions. We also wish to thank the several employees of the credit reporting agency that provided the data for the study who assisted us.

The second test uses changes in account ownership to proxy for changes in marital status. This test allows for several possibilities with respect to the role of personal trigger events. One possibility is that any change in marital status is a temporary negative adverse trigger event implying that the credit history score for an individual who has gone through a change will underpredict future credit performance. Alternatively, it may be that single and married individuals have different inherent propensities for adverse trigger events. If married individuals have better credit performance than comparable single individuals (perhaps because they have two incomes), then the credit history score of an individual who has gone through a divorce will overpredict future performance and the score for an individual who has just married will underpredict future performance.

The third test, which is performed with a subset of the sample, uses patterns in the timing of credit problems to identify generic, adverse, personal trigger events. Here, past credit problems that are isolated in time (clumped together) are treated as a proxy for a temporary adverse trigger event. If so, then we would expect the credit history scores of individuals with such patterns to under predict future credit performance.

The next section considers the construction of generic credit history scoring models and some of the statistical issues surrounding their use, particularly with regard to their treatment of situational data. We then describe the contents of credit reporting agency records and some of the major limitations of these data, particularly with regard to considering situational circumstances. The following section describes the specific variables and methodology used in our analysis. The ensuing section summarises our empirical results. The final section provides a discussion of the implications of our findings.

Statistical issues surrounding the use of credit history scores

The focus of this article is the question of whether the predictive accuracy of credit history scoring models could be improved with the inclusion of information about situational factors. Formally, we can represent the problem as follows. Suppose the true function for calculating the probability of default (delinquency) on a new loan for individual *i* from population *j* at time *t* is:

$$P_{i,j,t} = F_j(y_{i,j,t-1}, S_{i,j}, L_{i,j}) \tag{1}$$

where *P* is the probability of default; y is the individual's prior credit history; *S* represents a vector of situational factors related to personal circumstances; and *L* is a vector of regional or local market conditions (*S* and *L* may be past or contemporaneous). Credit history scoring models approximate the true function with a function G_j which relates the observed payment performance *D* of individuals *i*' in population *j* in a historical sample to ex ante predictive variables:

$$D_{i',j,t-1} = G_j(y_{i',j,t-2}) + e_{i',j,t-1} \tag{2}$$

where *e* is an error term. Our analysis considers the implications of the omission of *S* and *L* from such models.[2]

The failure to control for historical values of *S* and *L* in developing a credit history scoring model may assign weight to credit history variables that may more properly be attributed to situational factors. For example, by not including individual situational circumstances, the model would implicitly treat someone who performs poorly while experiencing a temporary health problem the same as someone with similar performance while healthy. Similarly, by not controlling for local economic factors, a credit history scoring model would assign the same risk level to a person who performs poorly during a

[2] Note that the credit scoring process can have other problems not considered here. For example, the credit history data used to apply the model to a particular individual, or used to estimate the model, may contain errors or inaccuracies or may be incomplete or ambiguous. That is, instead of using true values of *y*, mismeasured values may be used. Also, the function G_j may have been estimated over a different population *j*' than the population *j* to which the scoring model will be applied. For further discussion of these and other potential statistical problems, see Avery et al (2000).

recession (perhaps because he or she was unemployed) as to a person with similar performance during better economic times. It is not clear that these individuals should be expected to perform equally in the future. In general, the uniform application and development of credit history scores without regard to situational factors may result in a single score implying different "true" probabilities of future default depending on the individual's location or circumstances. The only instance in which the exclusion of *S* and *L* will not matter is when situational factors are highly persistent (for example, unhealthy individuals are always unhealthy) or when they have no relationship with credit payment performance.

The omission of *S* and *L* from credit history scoring models has two primary economic consequences. First, credit history scores will incorrectly rank the credit risk of individuals. Some marginal credit applicants will be provided either more or less credit than is appropriate, or these services may be inappropriately priced. Second, the credit screening process will be less efficient. Credit losses may be higher and institution profitability lower. These consequences are not restricted to explicit applications for credit. Many institutions introduce new products or special programmes using targeted mailings or other promotional campaigns that are limited in scope. These programmes often select individuals by a screening process based mainly on credit history scores.

Lenders could take actions that partially mitigate the problems stemming from omission of measures of *S* and *L* from scoring models. One response is to adjust cutoff levels based on past and expected future local economic circumstances. Another is to use underwriter judgment as well as credit history scores in credit underwriting, thereby taking into account some aspects of personal circumstances. For example, recognising that a major medical emergency may have led to payment problems with an otherwise good payment record might be viewed as a mitigating circumstance. While adjustments of these sorts may be made, they do not resolve the fundamental misspecification problem, particularly as it pertains to the estimation of credit scoring models.

While incorporating situational data into credit scoring models could help overcome these statistical problems, there are at least two impediments to doing so. First, information about the dates of occurrence of payment problems that would be needed to link to situational events is not always consistently recorded in credit records. Second, direct information on situational factors, such as health and employment status, is not included in the records at all. We elaborate on these issues below, starting with a discussion of the information contained in credit reporting agency records.

Contents of credit reporting agency records

Credit reporting agencies gather information on the experiences of individuals with credit, leases, non-credit-related bills, monetary-related public records, and enquiries and compile it in a *credit record*. The three national credit reporting agencies, Equifax, Experian and Trans Union, each attempt to collect comprehensive information on all lending to individuals in the United States.[3] The national credit reporting agencies receive information from creditors and others generally every month, and they update their credit records generally within one to seven days of receiving new information.[4]

To better understand the nature of credit files, the Federal Reserve Board obtained the full credit records (excluding any identifying personal information) for a nationally representative random sample of 248,000 individuals as of June 1999 from one of the national credit reporting agencies. A credit history score was provided for 203,000 individuals in the sample. The score was based on the credit reporting agency's proprietary scoring model as of the date the sample was drawn. This score is comparable to other commonly used consumer credit scores, with larger values indicating greater

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[3] Each of the three national credit reporting agencies has records on perhaps as many as 1.5 billion credit accounts held by approximately 190 million individuals, receiving more than 2 billion items of new information on these accounts each month. See "About CDIA" on the Consumer Data Industry Association website, www.cdiaoline.org.

[4] The credit record of an individual may differ across the three firms. Such differences may arise because rules regarding the linkage of reports to a common individual and the treatment of items such as non-current data can vary across credit reporting agencies. Further, the credit record of an individual may differ somewhat across the three companies because the timing of receipt of information differs among the three firms.

creditworthiness.[5] Also, although the individual's personal characteristics and address were not included in our sample, the census tract, state and county of residence were.[6] We also obtained the individual's date of birth (although the information was missing for many individuals).

Our sample (approximately one in 657 individuals with credit reporting agency records) contains virtually all the information that would be available for the estimation and application of a credit history scoring model. This includes four general types of information: (1) detailed information reported by creditors (and some other entities such as utility companies) on current and past loans, leases, or non-credit-related bills, each of which is referred to here as a *credit account*; (2) information derived from monetary-related public records, such as records of bankruptcy, foreclosure, tax liens (local, state or federal), garnishments, and other civil judgments, which we refer to as *public records*; (3) information reported by collection agencies on actions associated with credit accounts and non-credit-related bills (such as unpaid medical or utility bills), referred to here as *collection agency accounts*; and (4) the identities of individuals or companies that request information from an individual's credit record, the date of the enquiry, and an indication of the purpose of the enquiry.

Not every individual in the sample has information of each type. Indeed, individuals can be in credit reporting agency files for a number of reasons: having a record of a credit account, being an authorised user on a credit account, having a monetary-related public record, having a record of a collection action, or having had an enquiry about their credit circumstances. Approximately 87% of the individuals in our sample had a record of a credit account, and most of these — 92% — had an account that was open and active as of the date the sample was drawn. A very small share of the individuals with a credit reporting agency file had only a public record item or an enquiry. However, about 10% of the sample had a credit reporting agency file only because of a collection action.[7] The majority of information related to an individual's credit history is contained in credit account, collection agency and public record files, so we discuss these in more detail below.

Credit account information

Credit account records contain a wide range of details about each account. The data generally fall into five broad categories: account identification, account dates, account balances, account description, and payment performance. Each credit account record includes an account number, a unique identifier for each credit provider, and account ownership status (in particular, single or joint account or authorised user). Pertinent date information includes the date the account was established; the date it was closed or transferred (to collection or other major change in status); the date the account balance was paid down to zero; and the date when information was last reported to the credit reporting agency. The account records also provide current balance information, the largest amount ever owed on the account, the size of any credit limit applicable to the account and any amount past due.

Credit account records include a variety of account descriptive information, including identification of the type of account — for example, a closed-end loan (mortgage or instalment) or open-end loan (revolving, non-revolving, or cheque credit); and the nature or purpose of the account — for example, credit card, charge account, automobile loan, or student loan. Finally, the credit account record provides information on the extent of current and historical payment delinquencies extending back 48 months as well as information on other account derogatories. Payment delinquency information is recorded in four classes of increasing severity — 30 to 59 days, 60 to 89 days, 90 to 119 days, and 120 or more days past due. Other derogatories refer to accounts that have been charged off or are in collection, or those associated with a judgment, bankruptcy, foreclosure or repossession. Typically, accounts that are 120 or more days past due and accounts with other derogatories are grouped

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5 For a generic discussion of the development of credit history scores, see the website of Fair Isaac and Company, www.myfico.com.

6 Credit reporting agency files include personal identifying information that allows the companies to distinguish between individuals and construct a full record of each individual's credit-related activities. Files include the consumer's name, current and previous addresses, and social security number. Other personal characteristics sometimes found in credit files include date of birth; telephone numbers; spouse's name; number of dependents; income; and employment information. No other personal characteristic information is included in credit reporting agency files.

7 For details about the sample of credit reporting agency data, see Avery et al (2003).

together and termed “major derogatories” or “seriously delinquent”. Accounts with less severe delinquencies are typically termed “minor delinquencies”.

Public records and collection agency actions

In addition to personal characteristics and credit account information, credit reporting agency data include information derived from monetary-related public records and reports from collection agencies. Credit evaluators typically consider public records and collection agency actions to be adverse information on a par with credit account major derogatories when assessing the credit quality of individuals. The importance of these items is significant. Over one half of the individuals in our sample with at least one major derogatory (historical or current) did not have any credit account major derogatories; the only major derogatory items they had were collection agency actions or adverse public records.

Public record information includes records of bankruptcy filings, liens, judgments, and some foreclosures and lawsuits. The data distinguish (albeit imperfectly) between federal, state, and local tax liens and other liens. Otherwise, unlike credit account data, the public record data do not provide a classification code for the type of creditor or plaintiff. Although public records include some details about the action, such as the date filed, the information available is much narrower in scope than that available on credit accounts. Overall, about 12% of the individuals in our sample had at least one public record item, and almost 37% of the individuals with a public record item had more than one item noted.

Credit reporting agency records also include information on non-credit-related bills in collection that are reported by collection agencies. In some cases, collections on credit-related accounts also are reported by collection agencies rather than by the original creditor. In this case, the information is grouped with the collection actions on non-credit-related bills rather than with the credit account information. Overall, about 31% of the individuals in our sample had at least one collection action reported by a collection agency. The most common types of collection actions reported involved unpaid bills for medical or utility services.

Collection agency records include only limited details about the action, including the date acquired by the collection agency, the original collection balance, and an indicator of whether the collection has been paid in full. There is no code indicating the type of original creditor.

Impediments to incorporating situational data

Identifying the timing of a problem and its resolution is likely to be critical in modelling situational trigger events such as unemployment or a health problem. For most accounts, credit account records contain month-by-month payment performance histories going back several years from the date of most recent reporting (48 months in the case of the credit reporting agency that provided our data). Nevertheless, there are important limitations on the scope of the historical information contained in an individual’s credit record. Historical information on account balances and credit limits typically are not included, and information on past payment history is sometimes incomplete.

Incomplete information on payment history and the timing of delinquency episodes is a particular problem for credit accounts that are or have been seriously delinquent. In many cases no month-by-month payment histories are available for these accounts. For accounts that reached major derogatory status but ultimately were paid in full, often only the date the account was opened and the date the final payment occurred are recorded. For unpaid, seriously delinquent accounts, often only the date the account was opened and the date the consumer was prohibited from adding to the account (“date closed”) are recorded. While typically the “date closed” is likely to be near the date when the account first became seriously delinquent, this may not always be the case. Sometimes the “date closed” will be the date the account was transferred to a special collection department, or when a payment plan was established or was replaced by a new plan.[8] Such data limitations can make it difficult to tie the delinquency episode to pertinent economic data or to personal situational information, such as information on the timing of a job loss.

Even in the best of circumstances, information available on credit account balances is limited to the current balance, past due amount, and largest amount ever owed. Payment amounts and the amount owed when the account first became delinquent are not recorded. Thus, it is not possible to track performance using balance information. Further, there is evidence that even the limited balance information in the files may not be up to date for many seriously delinquent accounts.

As noted previously, even less information is available for public record items and collection agency actions than is available for credit accounts. The more limited information available on public records and collection agency accounts makes it even more difficult to track the historical circumstances associated with the actions. Importantly, for neither item is it possible to determine the timing of the original problem that ultimately led to the collection action or public record. There is also a lack of consistency in how collection agency actions are reported. A hospital may file a series of collection actions for each unpaid bill or one consolidated action.

Beyond the question of the timing of events, there are likely to be additional constraints on a credit scorer's ability to use situational information. Although general information about local economic conditions, such as county-level unemployment rates, is often available, it may be difficult to determine the location where an individual resided when payment problems arose. Obtaining more specific information about the economic circumstances affecting an individual, such as layoffs in the particular industry in which he or she is employed, represents even more of a challenge. Also, collection and public agency accounts lack codes to indicate the type of creditor involved in the action, which would facilitate evaluation of the circumstance that created the delinquency.

Finally, there may also be legal impediments to the use of situational data. The Equal Credit Opportunity Act and the Fair Credit Reporting Act place a number of important legal constraints on the content and use of credit reporting agency records.[9] This legal structure is intended to help ensure timely and accurate reporting, protect the privacy of individuals, and protect individuals in specified categories from unfair treatment.[10] In some cases, however, these legal constraints limit or prevent the use of certain types of situational information. For instance, our empirical analysis below demonstrates that changes in account ownership status bear importantly on predicted credit risk. Since change in account ownership may be systematically related to change in marital status, it may not be a permissible variable to include in credit scoring models.

These problems are hurdles that would have to be overcome if a modeller sought to develop a credit score that accounts for the timing of a credit problem and the speed with which it may have been resolved. They also represent impediments to our investigation of the potential value of situational information. Consequently, we can only imperfectly, and somewhat indirectly, test for the potential value of such data.

Empirical strategy

The goal of the analysis is to draw inferences concerning the potential value of incorporating situational data into credit evaluations. Our strategy for accomplishing this may be broadly summarised as follows. We first use the data to provide profiles of the credit history and payment performance for individuals in our sample for two periods: July 1997 to June 1999 (test period) and

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8 There are other limitations of the data beyond those emphasised here. For example, some credit accounts held by individuals are not reported to the credit reporting agencies. Further, current information is not always provided for each credit account reported. See Avery et al (2003) for further discussion of these issues.

9 The Equal Credit Opportunity Act (implemented by the Federal Reserve's regulation B) prohibits creditor practices that discriminate on the basis of race, colour, religion, national origin, sex, marital status, or age, as well as whether the applicant's income derives from a public assistance programme or whether the applicant has in good faith exercised any right under the Consumer Credit Protection Act.

10 See Bostic and Calem (2003) for a more detailed discussion of these laws.

prior to July 1997 (base period). A credit history score is estimated for each individual based on historical information in the individual's credit file as of the end of June 1997 (our estimated "historical credit score"). We then estimate two regression models designed to test three propositions regarding the potential importance of situational information in predicting credit performance.

Credit performance during the test period is measured by the actual payment history on new accounts opened after June 1997. The regression models relate performance on these new accounts to the individual's historical credit score and several proxies for situational factors. The sign and significance of the coefficients on the situational factor variables constitute our tests. A significant relationship would suggest that situational information is potentially useful for credit evaluation over and above the information contained in the credit score. We turn now to a more detailed description of this empirical strategy.

Empirical models and tests

We estimate two empirical models that provide tests of the potential value of situational factors in credit performance prediction, testing them on new accounts opened in July 1997 or later. The dependent variable for both models is a dummy variable equal to 1 if the account became delinquent 60 days or more (including entry to major derogatory status) by June 1999, and 0 otherwise.

The first model ("Model 1") tests the relation between local economic circumstances, as reflected in county-level unemployment rates, and payment performance on the new accounts. We include both the contemporaneous unemployment rate (UNEMP), calculated by averaging the 1997 and 1998 unemployment rates for the county, and the average unemployment rate over the prior two-year period, 1995 and 1996 (LAG_UNEMP).[11] If local economic circumstances matter, we would expect the likelihood of delinquency on the new accounts to be positively associated with the contemporaneous unemployment rate. In addition, we would expect an inverse association with the prior unemployment rate, because among individuals with the same historic credit score, those who reside in areas that experienced higher unemployment rates are likely to be better than average performers on new accounts (to the extent that local economic conditions do not persist).

The model additionally tests the relationship between payment performance on new accounts and patterns of account ownership. This is accomplished by distinguishing between individuals having mostly single accounts ("never married"), those with mostly joint accounts ("married"), and those who have migrated from having a substantial proportion of joint accounts prior to July 1997 to all, or nearly all, single accounts after ("divorced").[12] The model employs categorical variables distinguishing three groups of individuals defined as married in July 1997: those who were not married prior to July 1996 (NEW_MARRIED); those who were married prior to July 1996 but not prior to July 1995 (RECENT_MARRIED); and those who were married prior to July 1995 (OTHER_MARRIED). In addition, the model employs categorical variables distinguishing two groups of individuals defined as divorced in July 1997: those who changed their ownership patterns during the period July 1996 to June 1997 (NEW_DIVORCED) and all other divorced individuals (OTHER_DIVORCED).

Over the long term, individuals who have joint accounts may perform better than those who are solely responsible for their accounts, because they may have a second source of income to rely on in the event of an episode of unemployment or illness. Thus, those individuals classified as divorced or never married might be expected to have a higher likelihood of payment problems on accounts opened after June 1997 than those who have been married for some time (OTHER_MARRIED), all else equal. The expected short-term performance of those undergoing changes in status is less clear, however, in that it depends on the degree to which marriage, divorce or separation are trigger events affecting payment performance and the degree of persistence of any such effects. For example, if divorce tends to have a short-term adverse impact on financial stability, then newly divorced individuals would tend

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[11] It should be noted that the empirical analysis assumes that the individual's current county of residence has remained constant over the entire four-year period, although results are robust to using state-level unemployment rates in place of county-level rates.

[12] There may be reasons other than divorce for which an individual may migrate from having mostly joint to mostly single accounts, such as when a dependent child establishes his or her own accounts.

to have a relatively high likelihood of payment problems on new accounts, while those who less recently experienced a divorce that triggered credit problems might actually perform better than would be predicted on the basis of their credit scores.

The second model ("Model 2") tests the relation between payment performance on new accounts and the degree to which an individual's past payment problems "clump together" — that is, are isolated in time. In this test, we hypothesise that a temporary adverse trigger event is likely to create a pattern where all payment delinquencies occur at one time, in contrast to the dispersed pattern expected of a person with habitual problems. This represents a test of the importance of generic situational information, since the circumstances underlying the observed payment patterns are not known.

In estimating this model, we restrict attention to individuals that, in the past, had at least one minor delinquency but no serious delinquencies. The latter restriction is necessary because payment history patterns are missing for a substantial portion of the individuals with serious delinquency problems. The sample is restricted to individuals with at least some delinquencies since the objective of the test is to see whether differences in timing patterns in the occurrence of payment problems (which can be signals of one-time versus chronic behaviour) are related to future credit performance.

We calculate four categorical measures of dispersion as proxies for different payment problem patterns: one or more 30-day delinquencies all occurring within the same month during the base period (ONE_MTH); no delinquencies on any accounts outside a particular two- to five-month period (HALF_YEAR); no payment problems on any accounts outside a particular six- to 11-month period (ONE_YEAR); and payment problems stretching over one year or more (DISPERSED). To the extent that personal situational circumstances matter, we would expect more isolated payment problems to be a reflection of more transient adverse personal circumstances and, therefore, to be associated with reduced likelihood of delinquency on the new accounts.

In both Model 1 and Model 2, we control for the historical credit score (SCORE), the type of account for which performance is being evaluated (categorical variables REVOLVING, INSTALLMENT, MORTGAGE, and CREDIT_LINE), and the age of the account in months (ACCOUNT_AGE). Account type is included because propensity to default differs across account types, and account age is included because propensity to default tends to increase as new loans season. Finally, in each model, some additional control variables, such as borrower age category and the percentage minority population of the census tract, are included either in the base specifications or as robustness checks.

Construction of the credit history score

Ideally, we would want to control for the true credit history score for each individual as of June 1997 when investigating the role of situational circumstances. Unfortunately, we did not have access to the contemporaneous score; therefore, we rely on an estimated historical score. Since our objective is only to draw inferences about the potential role of situational factors rather than to precisely quantify their effects, we believe that our approximation is sufficient. Credit modellers would have access to contemporaneous credit scores and, therefore, would be able to better quantify the kinds of qualitative relationships we discuss here.

To estimate historical scores, we developed an empirical model of the credit history score by regressing the June 1999 scores included in the credit reporting agency data on contemporaneous characteristics of the individuals in the sample. The characteristics we chose to include were those that could also be measured as of June 1997 for the individuals in our sample. Notably, we were unable to include measures of balances, credit limits on credit accounts, or account enquiries. Key predictive variables included numbers of credit accounts in various stages of delinquency or in major derogatory status, variables derived from public records and collection agency accounts, and numbers of credit accounts of various types. The *R2* for the imputation regression equation was 0.87; proprietary considerations constrain our ability to report further details of the specification or estimation results.[13]

[13] Results reported in the next section are based on use of the same set of estimated historical scores for estimation of Model 1 and Model 2. As a robustness check, we estimated a separate score regression model for individuals who had experienced at least one 30-day delinquency but no serious delinquencies on credit accounts and used it to obtain estimated historical scores for use with Model 2. The results did not materially change.

The estimated regression model is applied to the individuals in the sample to obtain an estimated historical credit score for each individual using data that were in their credit file as of July 1997. In constructing the predicted score, we needed to make assumptions about the treatment of seriously delinquent credit accounts that had been opened before July 1997 since when they had first become delinquent was often unclear because of missing information in their payment history. If the account had been closed or the collection amount paid prior to July 1997, or if the date of last reporting was prior to July 1997, we assumed that it had become seriously delinquent prior to that date. Therefore, it was included in the calculation of the estimated historical credit score. Seriously delinquent accounts that had not been reported closed or were closed after June 1997 were excluded in computing the score, since we have no real way of determining the exact timing of the original payment problem associated with these accounts.[14,15]

Empirical test samples

The basic unit of observation in the samples used to estimate both models is new credit accounts opened in the test period between June 1997 and March 1999. We do not include accounts opened after March 1999 because of insufficient seasoning of such accounts as of the June 1999 date when the sample was drawn. We also exclude new credit accounts for which the individual is merely an authorised user and accounts of individuals who had applied for bankruptcy prior to July 1997. Finally, we also required the account owner to have at least one credit account open as of July 1995 (so that a historical credit score would be meaningful).[16]

These restrictions left us with a sample of nearly 310,000 accounts held by 109,660 individuals out of the original sample of 211,000 individuals with at least one credit account (other than an authorised user account). About two thirds of the individuals dropped from the analysis were thus treated because they did not have any new accounts. Only a small number, roughly 2,000 individuals, were excluded solely on the basis of prior bankruptcy. Since estimation of Model 1 requires information about the county of residence and information on county unemployment rates, which were missing for some observations, the final sample for Model 1 contained 254,630 accounts held by 90,357 individuals.

As noted earlier, the sample for Model 2 is further restricted to accounts of individuals who experienced at least one 30-day delinquency on an account prior to 1997 but had no seriously delinquent accounts, defined as 120-days delinquent or another major derogatory. These restrictions reduced the sample for Model 2 to 89,566 new accounts held by 32,299 individuals.[17] Nearly 4,000 of the excluded individuals had a seriously delinquent credit account; the remainder of those excluded had no record of a past payment problem on any credit account.

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[14] Eleven per cent of the individuals in the sample used to estimate Model 1 had a seriously delinquent account that was excluded on this basis.

[15] Collection agency accounts opened in July 1997 or later and public record items with a recording date in July 1997 or later were also excluded in estimating the historical credit score, with the exception of *credit-related* collection agency accounts and public record items dated July, August or September 1997. The latter were counted as seriously delinquent credit accounts, with the presumption that these items would have entered the individual's "true" score as of July 1997, but in the form of a delinquent credit account, which was subsequently transferred to a collection agency.

[16] A small number of credit accounts reported opened after June 1997 are identified as collection agency accounts, although the reporting on these apparently is by the original creditor (otherwise, they would appear among the collection agency accounts rather than among the credit accounts in the sample). An additional small number are identified as some type of workout or renegotiated account, such as a partial payment agreement. These accounts, although reported opened after June 1997, are excluded from the samples, since the recorded date opened potentially refers to the date the original loan was transferred to the collection agency or to the date the payment terms were renegotiated. Open-end non-revolving accounts opened after June 1997 were also excluded because previous research indicates that creditors frequently report such accounts only if they are delinquent.

[17] The third test does not require information about the county of residence for individuals; therefore, unlike the sample for Model 1, accounts of individuals whose county of residence was unknown were included in the sample for estimation of the base specification of Model 2.

Results

Variable definitions and descriptive statistics for the samples used to perform our tests are reported in Tables 1 and 2. Estimation results using ordinary least squares for the base specifications of the two models used for the tests are shown in Table 3.[18] Robustness issues are noted at the end of the section.

Results concerning local unemployment rates and account ownership

Model 1 provides evidence on two tests of the importance of situational factors for credit evaluation. The model examines the payment performance of new accounts opened in July 1997 or after. The first test draws inferences on the role of local economic circumstances as reflected in county-level unemployment rates. The second test draws inferences based on the relationship between performance on new loans and patterns of account ownership. In our sample, 6.9% of the new accounts were delinquent 60 days or more — a state henceforth, for convenience, to be termed "*default*" — at some date during the test period.[19] The sample mean values for county-level unemployment rates during 1995-96 and 1997-98 are 5.4 and 4.6, respectively, consistent with the robust state of the national economy during these years.[20] Sample mean values also indicate that one-third of accounts in the sample are held by individuals classified as never married, and about 10% are held by individuals classified as divorced.

Looking first at the control variables, we observe that the estimated historical credit score is strongly predictive of future performance on new accounts. Thus, for instance, on average for the sample, a 100-point decrease in the score raises the estimated likelihood of default by 1 percentage point. We also observe that the likelihood of default rises as an account seasons and varies by type of account, with mortgages, in particular, showing a much lower likelihood of default than other account types. Likelihood of default on a new account is also estimated to be highest for individuals in the age category "unknown" relative to those whose date of birth is recorded in their credit file. Finally, the likelihood of default increases substantially with the percentage minority population of the census tract, consistent with the notion that minority households may be more vulnerable to trigger events.

Turning to our main results, for our first test we find the contemporaneous unemployment rate is positively associated with estimated likelihood of default. For instance, an increase in the current county unemployment rate by 2 percentage points is estimated to raise the likelihood of default by about 0.3 percentage points. Further, the lagged unemployment rate is inversely associated with the estimated likelihood of default. An increase in the lagged county unemployment rate of 2 percentage points is estimated to reduce the likelihood of default by about 0.3 percentage points. These relationships are statistically significant and consistent with the view that credit performance, in part, is situational and depends on the economic environment.[21] Individuals with the same *ex ante* credit history score will perform differently if they reside in locations with differing local economic conditions. Moreover, the results indicate that credit history scores will tend to assign too high a probability of default to individuals who have resided in areas that are recovering from a local economic downturn.

Results pertaining to our second test, using account ownership to create proxies for marital status, are consistent with the view that credit performance in part is situational. Other factors held constant, long-term "married" individuals (OTHER_MARRIED) have an estimated 1.2 percentage point lower likelihood of default compared to "never married" individuals. This suggests that long-term "married"

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18 The estimations were conducted with the data weighted to account for account ownership status, with jointly held accounts receiving a weight of one half.

19 Estimated historical credit scores range between 360 and 781 with a median value of 673.

20 Lagged and contemporaneous unemployment rates range between about 1% and above 25%, with a 99% value of about 13%.

21 We addressed the high correlation between contemporaneous and lagged unemployment rates by evaluating the robustness of basic model results to the unit used to measure local economic conditions. Results were unchanged when unemployment rate variables were calculated at the state rather than the county level. Further, the estimated impact of the unemployment variables was robust to the statistical model employed (logit versus linear probability).

individuals are less vulnerable to income disruptions, possibly because they have two sources of income. Individuals who migrate from joint to single accounts during the year prior to July 1997 (NEW_DIVORCED), a likely indicator of being newly divorced or separated, exhibit the highest estimated likelihood of default on new accounts. These individuals have an estimated 2.2 percentage point higher likelihood of default compared to "never married" individuals, other factors held constant. Less recently "divorced" individuals (OTHER_DIVORCED) exhibit only slightly higher likelihood of default than "never married" individuals, suggesting that the adverse financial consequences of divorce or separation have both permanent and transitory components. Ultimately, the credit risk of a "divorced" individual (who does not remarry) does not revert to that of a "married" individual but becomes comparable to that of a "never married" individual.

"Newly married" individuals perform no differently from those who are "never married", while those who became "married" more than one year but less than two years prior to July 1997 (RECENT_MARRIED) actually exhibit the lowest likelihood of default on new accounts, all else equal. The latter result indicates that "recently married" individuals tend to perform better than would be predicted based on their credit histories, which reflect their performance when they were still "single".

Results concerning isolated episodes of delinquency

The second empirical model implements our third test based on the relationship between payment performance of new loans and the degree to which an individual's past payment problems are "clumped together". The sample mean value for the dependent variable indicates that 11.9% of the new accounts used to test Model 2 were in default at some date during the test period. This relatively high percentage of new accounts that experienced payment problems reflects our exclusion of individuals who had no prior delinquencies. Sample mean values also indicate that 26% of the accounts were held by individuals whose delinquency experience was confined to a single month, and 46% were held by individuals whose delinquency episodes were dispersed over a year or more.

Our measures of the degree of clumping of past payment problems are strongly related to future payment performance and exhibit the hypothesized signs. In particular, the likelihood of default is 8 percentage points lower for individuals with past payment problems all confined to a single month, and 4 percentage points lower for individuals with past payment problems confined to a two- to five-month period, as compared to individuals with payment problems dispersed over a period of a year or more. This result again is consistent with the view that situational circumstances matter for payment performance. Past payment problems that are isolated in time are probably associated with an adverse trigger event causing a temporary economic disruption for the individual, such as a temporary job loss or health problem. The results indicate that such past problems are less correlated with future payment performance than are past payment problems that are not isolated in time.

Robustness issues

Results were examined for robustness in several ways. To begin with, we explored inclusion of a variety of additional control variables. In particular, we re-estimated Model 1 controlling for each of the nine US Census divisions using a set of dummy variables. The findings in this case broadly support the role of situational factors related to local economic conditions. Compared to an individual residing in the Pacific division, individuals in most of the other regions were estimated to have a likelihood of default on new accounts roughly a full percentage point larger. The sole exception was the East South Central division, for which individuals had a substantially higher likelihood of default on new accounts (about 2.4 percentage points higher than individuals in the Pacific division). These patterns are broadly consistent with cross-region patterns of unemployment and other economic circumstances.[22] The best performing division, the Pacific, had relatively high lagged average unemployment rates.[23]

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[22] After inclusion of the Census division dummy variables, the local unemployment rate variables were not statistically significant but retained the same signs as in the base specification. Results for other independent variables were not materially different from those reported in Table 3.

[23] The sample average of 1995-96 unemployment rates for the Pacific division was 7.1%, while for other Census divisions it ranged from 3.9 to 5.8%. The gap was smaller for the 1997-98 average unemployment rate, which was 5.8% in the Pacific division and ranged from 3.3 to 5.1% in other Census divisions.

The worst performing division, the East South Central, had consistently been the poorest (lowest per capita income), although its lagged and contemporaneous average unemployment rates were not particularly high or low.[24]

Inclusion of other control variables in either model did not change the results in any substantial way. For instance, additional control variables for Model 2, in general, are not statistically significant and have little impact on the results from the base specification. Similarly, results from the base specification of Model 1 change little when categorical variables controlling for relative median income of the census tract where the individual resides are added to the model. In this case, we find that the likelihood of default is 1.6 percentage points higher in lower-income tracts (those with relative median income of 80% or less) compared with upper-income census tracts (relative median income of 120% or more).

We also estimated the models using an estimated historical credit score that was calculated for each individual as of December 1996 instead of June 1997. This was done in order to mitigate potential simultaneity between elements of the estimated historical score and the dependent variable. For instance, it is conceivable that some of the new accounts recorded as opened after June 1997 and that involve a major derogatory are actually transferred or renegotiated older accounts. The results were not materially different from those reported in Table 3.

We also restricted the sample used to estimate Model 1 to accounts of individuals for whom there was no ambiguity about including a seriously delinquent account in estimating their historical credit score (no seriously delinquent account with a reported date closed after June 1997). Again, results were not materially different. Finally, the results were found to be robust to using logistic regression in place of ordinary least squares.[25]

Conclusions

Credit scoring benefits both lenders and borrowers. The failure, however, of credit history scoring models to consider situational information relating to the economic and personal circumstances of individuals raises important statistical issues that may affect the ability of such scoring systems to accurately quantify the credit risk of individuals. This paper examines the potential value and some of the practical limitations associated with incorporating situational data into credit risk evaluations.

Our empirical models yield strong inferences that situational circumstances influence an individual's propensity to default on a new loan, holding constant the credit quality of the individual as reflected in an estimated *ex ante* credit history score. We demonstrate that the likelihood that an individual will default on a new loan depends on contemporaneous economic conditions in the area where the individual resides. Moreover, we find that the individual's *ex ante* credit history score will overstate the likelihood of default on the new loan in areas that are recovering from an economic downturn and understate such risks in areas that have been experiencing exceptionally strong economic conditions. Our results related to account ownership are also consistent with the view that credit performance is dependent on individual situational factors. This view is further supported by evidence that the likelihood of default on a new loan is smaller than indicated by the credit score when past credit problems were isolated in time. Together, these results suggest that adverse, temporary economic or personal shocks, such as income disruptions, are important factors influencing payment performance even after accounting for an individual's *ex ante* credit quality.

Failure to account for situational factors of any type is not neutral. Those subject to adverse situational changes are likely to be directly penalised by failure of credit score modellers to account for these

24 For instance, the sample average of 1997-98 per capita income was USD 22,603 dollars in the East South Central division and ranged from USD 24,307 to USD 31,426 in other Census divisions.

25 The only qualitative distinction between the logit and ordinary least squares results concerned the relationship between age of the individual and likelihood of default, where the logit analysis indicated an inverse relationship between age and likelihood of default among those with age recorded.

factors. Other parties also bear costs to the extent that models are misspecified. Such costs can involve additional credit losses, higher prices for credit, and unnecessary rejections of credit.

Currently, there is some use of situational information in the credit evaluation process. Judgmental review is the traditional approach to incorporating situational information and plays a particularly important role in residential mortgage underwriting. Custom models developed for specific banking institutions dealing only with local markets inherently incorporate geographical situational factors. Lenders have traditionally also varied cutoffs on scores to adapt to regional or national business cycles. Further, there is no statistical impediment to incorporating local economic data into the scoring process, since such data are publicly available on a timely basis. However, generic credit history scoring models that are often the primary basis for lending decisions for credit cards, automobile loans and other types of consumer credit do not factor in local economic circumstances. One possible reason why local economic conditions are not considered is uncertainty about prior locations of residence of individuals.

Making full use of situational information requires data on individuals' specific circumstances that, in many cases, are not available within credit reporting agency data. Our analysis does suggest that some information on situational circumstances can be gleaned just from information in individuals' own credit histories. For example, our analysis of Model 2 relied on information concerning the timing of individuals' credit problems but was implemented using only a restricted portion of the sample. Implementing such approaches more broadly would require more detailed information on the timing of major derogatory credit problems than may be available in credit reporting data. Determining when payment problems were first encountered on major derogatory credit accounts may be difficult in many cases, particularly if the account was transferred to a collection agency or ended up as a public record action. In addition to these technical considerations, there may be legal constraints on the kinds of individual situational information that can be used. For example, marital status cannot be used under the rules established by the Equal Credit Opportunity Act.

Clearly, modellers and credit evaluators have to weigh the costs and benefits of considering economic and individual situational information, and there are strong competitive incentives for credit evaluators to use such data when the benefits outweigh costs. It is important to note that some of the costs may be high because of legal constraints on information that can be used in scoring models, and the fact that the United States. has a voluntary credit reporting system subject to a particular set of institutional and legal rules. There are important reasons for having such a system (Hunt (2002)). Nevertheless, our analysis suggests that there are potential benefits from expanding the use of situational information. Thus, a question for future research is whether modifications in the structure of the credit reporting system could be made, to permit increased use of individual situational information that would yield greater accuracy in prediction and lower average credit losses and cost of borrowing.

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Table 1
Variable definitions

Variable	Definition
DEFAULT	Dummy (0/1) variable = 1 if account became 60 days or more delinquent by June 1999
UNEMP	Average unemployment rate over the two-year period 1997-98 in the county where the individual resides
LAG_UNEMP	Average unemployment rate over the two-year period 1995-96 in the county where the individual resides
NEW_MARRIED	Dummy (0/1) variable = 1 if the individual satisfies the criterion for married[1] as of July 1997 but not July 1996
RECENT_MARRIED	Dummy (0/1) variable = 1 if the individual satisfies the criterion for married[1] as of July 1997 and July 1996 but not July 1995
OTHER_MARRIED	Dummy (0/1) variable = 1 if the individual satisfies the criterion for married[1] as of July 1997 and July 1996 and July 1995
NEW_DIVORCED	Dummy (0/1) variable = 1 if the individual satisfies the criterion for divorced[2] as of July 1997 but not July 1996
OTHER_DIVORCED	Dummy (0/1) variable = 1 if the individual satisfies the criterion for divorced[2] as of July 1997 and July 1996
NEVER_MARRIED	Dummy (0/1) variable = 1 if the individual does not satisfy the criterion for married[1] or divorced[2] as of July 1997
ONE_MTH	Dummy (0/1) variable = 1 if the individual's recorded minor delinquencies all occurred in the same month
HALF_YEAR	Dummy (0/1) variable = 1 if the individual's recorded minor delinquencies all occurred within an identifiable two- to five-month period
ONE_YEAR	Dummy (0/1) variable = 1 if the individual's recorded minor delinquencies all occurred within an identifiable six- to 11-month period
DISPERSED	Dummy (0/1) variable = 1 if the individual's recorded minor delinquencies occurred over 12 months or more
SCORE	Estimated historical credit score
REVOLVING	Dummy (0/1) variable = 1 for revolving accounts
INSTALMENT	Dummy (0/1) variable = 1 for instalment accounts
MORTGAGE	Dummy (0/1) variable = 1 for mortgages
CREDIT_LINE	Dummy (0/1) variable = 1 for line-of-credit accounts
ACCOUNT_AGE	Number of months since account was opened
AGE1, AGE2 and AGE3	Set of three dummy (0/1) variables classifying individuals by age: under 40, 40-64, and 65 or older
AGE_UNKNOWN	Dummy (0/1) variable = 1 if the individual's date of birth is not provided in the data
MINORITY_PCT1 to MINORITY_PCT4	Set of four dummy (0/1) variables classifying the census tract where the individual resides by percentage minority population: ≤ 10%, 10-50%, 50-80%, and ≥ 80%
MINORITY_UNKNOWN	Dummy (0/1) variable = 1 if the minority population of the census tract where the individual resides is unknown

[1] An individual is defined as married as of a specified date if the individual has at least one jointly held account per five accounts open as of that date, or a total of four or more such accounts.

[2] An individual is defined as divorced as of a specified date if the individual does not satisfy the criterion for married as of that date; one or more of the individual's accounts were closed prior to the date; and at least one out of three of these closed accounts was jointly held.

Table 2
Sample descriptive statistics[1]

Variable name	Sample for Model 1		Sample for Model 2	
	Mean	Std dev	Mean	Std dev
DEFAULT	0.069		0.119	
UNEMP	4.622	2.008	4.714	2.085
LAG_UNEMP	5.384	2.096	5.476	2.186
NEW_MARRIED	0.062		0.066	
RECENT_MARRIED	0.066		0.072	
OTHER_MARRIED	0.453		0.487	
RECENT_DIVORCED	0.006		0.006	
OTHER_DIVORCED	0.086		0.080	
NEVER_MARRIED	0.328		0.291	
ONE_MTH	.		0.263	
HALF_YEAR	.		0.166	
ONE_YEAR	.		0.114	
DISPERSED	.		0.457	
SCORE	647.8	64.09	595.5	62.68
REVOLVING	0.620		0.538	
INSTALMENT	0.293		0.383	
MORTGAGE	0.071		0.065	
CREDIT_LINE	0.016		0.014	
ACCOUNT_AGE	13.70	5.266	13.65	5.30
AGE1	0.305		0.302	
AGE2	0.370		0.372	
AGE3	0.067		0.050	
AGE_UNKNOWN	0.258		0.277	
MINORITY_PCT1	0.435		0.335	
MINORITY_PCT2	0.335		0.280	
MINORITY_PCT3	0.055		0.055	
MINORITY_PCT4	0.045		0.050	
MINORITY_UNKNOWN	0.130		0.280	
Number of observations	254,630		89,566	
Weighted number of observations	213,603.4		75,426.1	

[1] Means and standard deviations are weighted with joint accounts receiving a weight of one half. Standard deviations are not given for dummy (0/1) variables.

Table 3

Linear probability regression results for default on new accounts

Dependent variable: default

Independent variables	**Model 1**		**Model 2**	
	Coefficient estimate	**T-statistic**	**Coefficient estimate**	**T-statistic**
UNEMP	0.0015	2.06*		
LAG_UNEMP	-0.0015	2.12*		
NEW_DIVORCED	0.0509	7.84**		
OTHER_DIVORCED	0.0342	13.77**		
NEVER_MARRIED	0.0294	14.26**		
NEW_MARRIED	0.0296	10.96**		
OTHER_MARRIED	0.0178	8.91**		
ONE_MTH			-0.0810	30.91**
HALF_YEAR			-0.0394	12.90**
ONE_YEAR			-0.0202	5.72**
SCORE	-0.0010	137.40**	0.0000	0.26
CREDIT_LINE	-0.0070	1.80	-0.0404	4.35**
INSTALMENT	-0.0113	10.17**	-0.0069	3.04**
MORTGAGE	-0.0221	11.60**	-0.0606	13.74**
ACCOUNT_AGE	0.0042	50.11**	0.0074	40.03**
AGE1	-0.0161	12.33**		
AGE2	-0.0204	16.54**		
AGE3	-0.0142	6.79**		
MINORITY_PCT1	-0.0102	6.51**		
MINORITY_PCT2	-0.0020	1.23		
MINORITY_PCT3	0.0241	9.81**		
MINORITY_PCT4	0.0399	15.13**		
INTERCEPT	0.6644	115.60**	0.0527	5.36**
Number of observations	254,630		89,566	
Model R^2	0.096		0.030	

* Significant at the 5% level.

** Significant at the 1% level.

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