Microcredit Client Risk Profiling

by

Colin D. Nicholson

Bachelor of Science in Biochemistry with High Honors,
Carleton University (1985)

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Signature of Author: ___________________________________________ Alfred P. Sloan School of Management
May 7, 2004

Certified by: ___________________________________________ Richard M. Locke
Alvin J. Siteman Professor of Entrepreneurship and Political Science
Thesis Advisor

Accepted by: ___________________________________________ Stephen Sacca
Director, Sloan Fellows Program
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Abstract

Analysis of new and renewing microborrower risk behaviors at the Mexican microfinance institution FinComun shows that risk behavior can be predicted. The range of risk behaviors analyzed include: incidence of late payments, maximum number of weeks in arrears, and default. Males generally exhibited somewhat riskier patterns of credit behavior than females. Tools are provided for defining and predicting risky credit behavior. The implication is that these tools can be used to improve the management of credit risk and, therefore, improve the effectiveness of the microfinance program.

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Of course all things erroneous or inaprops in this work are my sole responsibility.
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**Introduction**

Microfinance\(^1\) may be described as the provision of banking services to the poorest segments of society using unconventional risk assessment and client service techniques. Often considered to be a modern development intervention, microfinance is actually well documented and researched from the beginnings of the industrial revolution forward: from 18\(^{th}\) and 19\(^{th}\) England in the form of bequest funds for loans to young entrepreneurs; from early 19\(^{th}\) century Ireland in the form of famine relief lending funds; and from mid 19\(^{th}\) century and forward Germany in the form of urban credit cooperatives (Hollis & Sweetman, 1998). Modern microfinance substantially dates from the 1970’s and there are now estimated to be more than 10,000 microfinance institutions worldwide (Economist, 1999). The older, exemplar institutions are generally considered to be the Bangladeshi Grameen Bank (Hassan, 2002), the Bank Rakyat Indonesia unit desai division (Robinson, 2001), and the Bolivian BancoSol (Navajas et al, 2000).

The provision of microfinance has been of interest in the development field as a potential alternative to the provision of straight cash subsidies (Morduch, 1999). It has also been touted to be a peculiarly effective means of enhancing the economic and social status of women (Mahmud, 2003) who have generally been observed to be better microlending risks than men (Barr & Kinsey, 2002). From the economic perspective the interest of microfinance lies in its novel mechanisms for adequate risk assessment and effective client service (Townsend, 2003). The development and economic perspectives

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\(^1\) Strictly speaking, microfinance is the provision of small scale loans for investment purposes with payment substantially deferred until the investment matures. Microcredit is the provision of small scale loans with regularly scheduled payments of interest and principal. Microsavings is the provision of small scale savings/investment instruments. FinComun, the subject of this paper, provides microcredit and microsavings services for its clients. In this paper, unless otherwise indicated, the term microfinance is used to refer the suite of microfinance proper, microcredit and microsavings.
come together, or rather collide, in a current popular controversy over the actual social effectiveness and long term sustainability of microfinance institutions (Jain & Moore, 2003).

One thread of thought within this controversy holds that *business process* effectiveness within microfinance institutions enhances their *social effectiveness* (Jain & Moore, 2003). That is to say, the most efficiently run microfinance institutions have the biggest social impact. This paper documents a work undertaken in the spirit of this perspective. A credit risk evaluation tool was developed for the Mexican microcredit and microsavings institution FinComun from field research undertaken in January of 2004. The tool assesses the likelihood of microborrower delinquency – late payment, number of weeks in arrears, and default - for new microborrowers as a function of free cash flow and for renewing microborrowers as a function of past credit behavior. Gender differences in these microborrower behaviors are also evaluated.
FinComun

The Mexican microfinance institution FinComun, Servicios Communitarios S.A. C.V. Union de Credito was founded in 1994 as an enterprise of the Juan Diego Foundation (FJD). Other than FJD, major capital contributors to FinComun include Grupo Bimbo, S.A.; the Inter-American Development Bank (IDB); and the Inter-American Foundation (IAF). The stated mission of FinComun as follows.

To contribute to the integral development of people, with an emphasis on those with scarce resources, through the offer of community financial services that will help to resolve the structural causes of poverty and offer services sustained by productivity, quality, profitability, professionalism and a firm base of institutional values—these will be offered in a manner accessible to all, with personalized treatment, modern technology, low transaction costs, and technically capable and morally formed collaboration (James, 2002).

Practically speaking, FinComun seeks to stimulate entrepreneurial activities in the segment of society in the Federal District of Mexico—that is, Mexico City—with incomes of less than US$2.1 per day. Entrepreneurs in this segment have traditionally been underserved by the formal banking sector due to a combination of the perceived unprofitability of serving them, their undocumented/unofficial status, and deep seated biases within the Mexican socio-economic milieu.

FinComun currently operates 17 branches with 220 employees. Of its approximately 35,000 clients 27,700 hold microsavings accounts, with value in excess of US$2 million; 14,000 hold current microcredits, with value of approximately US$8.3

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2 The Juan Diego Foundation (FJD) was itself founded in 1991 by, among others, members of the prominent Servitije family and the Grupo Bimbo S.A., a major producer/distributor of baked goods. The FJD is a "community of persons whose purpose is to look for and support solutions to eradicate the structural causes of poverty in Mexico." (James, 2002).

3 A multilateral development bank that provides financing for economic, social and institutional projects in Latin America and the Caribbean.

4 An independent agency of the U.S. government providing development grants for innovative, sustainable, and participatory self-help programs to NGO’s and community-based organizations in Latin America and the Caribbean.
million; and 1,200 hold investment accounts\(^5\). Microsavings accounts can be opened with as little as the equivalent of US$1 and pay interest of 5% p.a.\(^6\) Microcredits start at the equivalent of US$25 and range to US$3,000 with an average initial principal of US$1,000. A total of 65% of credits have terms of 16 weeks, 25% have terms of 24 weeks. Interest is charged at a monthly rate of 6% on declining balance\(^7\). A slight majority – 55% - of FinComun’s clients are female.

Perhaps unique among microfinance institutions, FinComun makes extensive field use of handheld computing technology to assess and monitor clients. This has resulted in an extensive database of clients and their credit behavior. The key objective of this work was to analyze this database and develop risk profiling tools that could be used by FinComun to better assess the credit worthiness of both new and renewing clients. The work builds upon FinComun’s long standing philosophy of offering services that are sustained by productivity and profitability.

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\(^5\) These include NGOs, churches etc. seeking “ethical” investment opportunities.

\(^6\) The inflation rate in Mexico in the period late 2003 early 2004 was approximately 3.5%.

\(^7\) In the informal credit market interest is charged at a monthly rate of 10% on initial balance.
Mechanisms: How and Why Does Microfinance Work?

Provision of small value banking services to the poor on a large scale using conventional banking techniques – credit references, collateralization, etc. – would generally be considered unviable at less than usurious rates of interest due to the fact that microlenders’ transaction costs far outstrip their interest revenues. Indeed, in settings where clients are undocumented, transient and without secure rights to collateralizable fixed assets banking should be all but impossible. Nevertheless, microfinance institutions currently operate within these constraints. The three microfinance mechanisms that are generally held to account for this paradox are: (1) group lending, (2) regular payment schedules, and (3) progressive lending (Morduch, 1999).

Group Lending

In group microlending, a small number of peers together assume responsibility for the microcredits of any one individual in the group. In the strongest forms of group microlending, only one microborrower in the group at a time is permitted to hold an outstanding microcredit and all members of the group are held responsible for its repayment. The default of any individual microborrower in the group disqualifies all members of the group from receiving future microcredits.

Townsend (2003) rigorously evaluates the mechanisms that might underlie both group and individual microlending practices. As compared to individual microlending, several economic models of group microlending predict higher microborrower repayment rates. Essentially, the microlender co-opts the microborrower group for the purpose of selection and monitoring. Ex ante mechanisms of this co-opting include a reduction in moral hazard due to improvements in the screening of both microborrowers (Ghatak,
1999; Amendariz de Aghion & Gollier, 2000) and investment choices (Stiglitz, 1990).
The microlender relies on the members of the microborrowing group to self-select
individual credit worthy microborrowers and to self-screen individual credit worthy
investments. This is critical where either the extent of the microlender’s knowledge of
individual microborrowers is limited – for example, if they are undocumented – and/or
where the costs to the microlender of prescreening each microborrower and each
investment exceeds the expected interest revenues.

*Ex poste* mechanisms of this co-opting include effective improvements in both
monitoring (Banerggee, Besley & Guinnane, 1999) and pressure for repayment (Besley &
Coate, 1995). Group members have an incentive to monitor their peers for diligent
pursuit of investment projects and will tend to join groups on the basis of the ease – in
terms of time and travel – of monitoring each other. Groups will typically also have
access to socio-cultural means for exerting repayment pressure that are not available to
the microlender; for instance, shaming and shunning.

Notwithstanding the above, the benefits of group as opposed to individual
microlending for any one prospective microborrower-microlender pair will vary and can
result in a preference for the individual microcredit. So, to the extent that an individual’s
good credit worthiness is readily demonstrable to a prospective microlender then the
screening benefit of the group structure - accruing to the microlender - is reduced.
Further, the credit worthy individual, by drawing an individual microcredit, can avoid the
personal costs of both monitoring group members and pressuring them for repayment
(Holmstrom & Milgrom, 1987). Conversely, when average individual wealth within a
group is small relative to the size of repayments – i.e., there is a high risk of default –
then the group mechanisms described above could be particularly valuable to both microborrower and microlender; further, large differentials in wealth – *viz* power - within a group could strengthen intragroup monitoring effectiveness (Prescott & Townsend, 2002).

Group microlending is typically the component of microfinance that receives the most popular attention; nevertheless, even within the flagship group microlending programs - Grameen and BancoSol - migrations of the “better off poor” towards individual microlending is observed. For microfinance programs in the more industrialized developing countries – for example, Eastern Europe and Russia – individual microlending tends to predominate (Amendariz de Aghion & Morduch, 2000). These patterns are exactly predicted by the theories of mechanism design described above.

FinComun issues substantially only individual microcredits (95% of total number). Presumably this is because its clients – small business owner/operators in Mexico City – rank within the “better off poor”.

**Regular Payment Schedules**

The typical purpose of a microloan is productive investment. In conventional banking such loans would generally not be repayable until the investment had matured. However, regular installment payments of both interest and principal are almost universally employed by microfinance institutions.

Several mechanisms have been suggested for the effectiveness of regular payments. Because payments require interaction of the institution with the client, they carry information about the microborrower to the microlender and, as such, minimize some of the microlending risk (Amendariz de Aghion & Morduch, 2000). On a gross
level, the microborrower who comes to make a payment has clearly not fled the district. On a finer level, microlenders can use the payment transaction as an opportunity to make enquiries about the health of the investment. Poor clients, for whom the opportunity cost of time is presumably low, may be more willing than wealthier clients to take the time, and make the effort, for a regular trip to the institution. On the other hand, FinComun reports that a common complaint of clients is the amount of time required to make a trip to the local branch office for repayment. This report reinforces the notion that, compared to the prototypical microfinance institution, FinComun is serving the “better off poor” for whom the opportunity cost of time is relatively far from zero.

The fact that payments must be made before income is realized from the productive investment means that clients must be accessing either regular household income or other credit sources to make payments. In the former case, the microcredit could de facto be playing the role of a savings service otherwise not available (Rutherford, 2000). That is, if regular household income cannot be saved for future investment because savings services are absent or inaccessible, then a microcredit is a valuable alternative. Reasons for absence or inaccessibility of saving services range from minimum deposit requirements in conventional banks to the inability of income earners, especially women, to negotiate a disciplined savings program within the household.8

Microfinance clients often also use informal sources of credit: family, friends, and moneylenders. Jain & Mansuri (2003) in a survey of Bangladeshi microborrowers found that 73% also borrow informally while Zeller & Sharma (1998) in a survey of Bangladeshi and Pakistani microborrowers find 66% and 37% respectively utilizing the

8 FinComun was actually founded as an offshoot of a rural bakery cooperative because local women began to approach the managers with requests to hold for safe keeping their surplus household funds which otherwise would have been used by their husbands for the purchase of alcohol.
informal credit market. If a productive microcredit financed investment has not matured and other household income is not available for regular payments then these sources of informal credit, with presumably higher monitoring intensity and effectiveness, will be accessed by the borrower (Jain & Mansuri, 2003). To the extent that this occurs microfinance institutions are effectively co-opting the monitoring potential of these informal credit sources.

Progressive Lending

Progressive lending, by which a microborrower in good standing is guaranteed a follow-on microcredit of higher value and/or with a reduced intensity approval process is the third major mechanism to which microfinance success is ascribed. FinComun practices both of these forms of progressive lending.

The mechanism for progressive microlending is straightforward. When clients are either highly mobile and/or their credit history does not readily travel with them over time and space, and when a variety of credit sources are available then the client has a motivation for “strategic default”; that is, to default to one microlender in favor of accessing credit at a second microlender. A promise by the microlender to increase future loans in the event of good credit behavior militates against this motivation (Amendariz de Aghion & Morduch, 2000).

Miscellaneous Mechanisms and Program Factors

Collateral requirements are not uncommon in microfinance programs, including FinComun. In general, however, the most valuable collateral for microlenders in microfinance is not that which has a high resale price but rather for that for which the potency of the threat of seizure is high. In economic terms, typical microfinance
collateral has a higher utility for the microborrower than for the microlender (Churchill, 1999).\footnote{In support of this notion, FinComun reports that televisions are the best collateral. When collection agents attempt to seize televisions in lieu of payment, clients typically request that another household appliance – for example, refrigerator – be seized instead.}

Non-credit program aspects - for example, vocational training – have been touted as important for the social effectiveness of microfinance. At the Grameen bank, these aspects have been found to have a significant positive effect on microborrowers’ investment returns (McKernan, 2002). FinComun, however, reports negative experiences with clients who blame poor vocational training for poor investment outcomes. Such clients then use the excuse of poor vocational training for non repayment.
Effectiveness: Does Microfinance Benefit the Poor?

The key current issue in the field of microfinance is whether or not it actually benefits the poor. This issue is all the more acute in light of the fact that the majority of microfinance programs are not profitable; i.e., they are not justifiable on business terms alone. Of the 188 institutions reported in the most recent Microbanking Bulletin, 65 are self defined as financially sustainable and report data in support of this, the remaining nearly two thirds fall short of financial sustainability by a significant margin (Microbanking Bulletin, 2003). That is to say microfinance is, after all, substantially just another means of delivering a subsidy to the poor in the developing world.

Whether or not this subsidized microborrowing is a net benefit or net penalty for the poor, remains controversial. Morduch (1999) lucidly enumerates the assumptions, many yet untested, that speak to this controversy. Subsidized microborrowing could be of net benefit for the poor if the following assumptions obtain.

- There is a high positive social value on consumption by poorest; i.e., the social value of consumption increases as wealth decreases.\(^{10}\)

- There is a high price – i.e., interest rate – elasticity of demand for credit; i.e., an increase in interest rates drives a disproportionate number of the poor out of the market for credit.

- Low interest rates promote high risk, high payoff investments; i.e., major improvements in poverty will best be achieved through high risk/high payoff investments, and these investments are preferentially undertaken by microborrowers when interest rates are low.

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\(^{10}\) Note that this assumption is critical to an evaluation of the benefits of any type of subsidy to the poor, not merely subsidized credit.
Informal market rates are unaffected or even depressed due to competition from subsidized microcredit; \textit{i.e.}, moneylenders are either driven from the market or forced toward less usurious lending practices.

On the other hand, subsidized microborrowing could be a net penalty for the poor if the following alternate assumptions obtain.

- There is a relatively flat social value on consumption across income levels.
- There is a low price – \textit{i.e.}, interest rate - elasticity of demand for credit.
- Low interest rates promote low risk, low payoff investments.
- Informal credit market interest rates increase as the lowest risk microborrowers are “skimmed” out of the system by subsidized microlenders.

The extent of current controversy over effectiveness is manifest in the fact that even the most appropriate \textit{form for the objective study} of effectiveness is not settled (Hulme, 2000; Morduch, 1999).

Nevertheless, in the face of this controversy some studies, in particular of Bangladeshi microfinance programs purport to find evidence of substantial effectiveness, and substantially superior effectiveness as compared to more conventional subsidy programs. Kandker (1998) finds a $1.00 benefit to female microborrowers for every $0.91 cost to microlenders. Pitt & Kandker (1998) find the same $1.00 benefit to male microborrowers comes at a less favorable cost of $1.48 to microlenders; however, even for men, microfinance compares favorably to conventional food-for-work programs that cost $1.71-2.62 for every $1.00 of benefit.

Of particular relevance to the theme of this thesis are the studies summarized by Hulme & Mosley (1996) that together show a strong positive correlation between
financial sustainability and effectiveness. The authors surveyed a range of South Asian, Latin American, and African microfinance programs in the period 1988 through 1992. The chosen metrics were the subsidy dependence index (SDI)\(^ {11}\) devised by Yaron (1991) for financial sustainability, and the relative annual average change in family income\(^ {12}\). All of the programs surveyed improved the annual income of clients relative to a matched control group; however, a clear positive correlation between efficient business practices — i.e., relative subsidy independence — and the relative annual average change in family income was shown. That is to say, good business brings good social outcomes.

**Figure 1.** Data from Hulme & Mosley (1996) Table 3.3 for factor by which interest charged would need to rise if subsidies were removed; Table 4.1 for annual rate of client income growth, relative to control group.

\(^{11}\) Defined as the factor by which the microcredit interest rate would need to be raised in order for an institution to cover its operating costs if all subsidies were removed. A value less than 1.0 indicates that the institution is making a profit without any subsidies; a value of 1.0 indicates that the institution is just breaking even; a value greater than 1.0 indicates that the institution would need to raise its interests rates in order to break even if subsidies were removed.

\(^{12}\) Defined as the annual average change in family income of microcredit clients divided by the annual average change in family income of a matched control group of non-borrowers.
Methodology

Field research was conducted on site at FinComun’s office in Mexico City from 4 through 16 January, 2004. The research consisted of interviews with the Executive Director and Chief Operating Officer during which the need for an enhanced credit risk evaluation tool was identified. An extensive extract from the Fincomun database was then analyzed for this purpose.\(^{13}\)

This section reviews in detail the analysis of an extract of records from FinComun’s database. The objectives of the analysis were as follows.

1. Develop a model for predicting the risky credit behaviors: late payments, maximum number of weeks in arrears, and default.

2. Identify gender based differences in credit risk behaviors.

The analysis represents an example of an analytical customer relationship management (CRM) exercise. The tools used for this analysis were the spreadsheet package Microsoft® Excel 2002 and the statistical package Eviews4.1 (Quantitative Micro Software, www.Eviews.com). These packages are adequate for the task; however, a dedicated stand alone database mining software package or a database mining module within a broader CRM software package could be more efficient for regular analyses of this type by FinComun.

\(^{13}\) Supplementary investigations, beyond the scope of this thesis were also undertaken. These included: reviewing the work flow for credit approval; undertaking a preliminary review of the range of commercial customer relationship management (CRM) software packages that are available and that could meet FinComun’s needs for improved control of credit approval work flow; interviewing clients and conducting a client survey for the purpose of identifying unfulfilled financial service needs; analyzing the viability of a new home improvement loan financial service; and identifying prospective buyers of a home improvement loan financial service from amongst the current client base.
Data Manipulations for Predicting Risk Behavior of Renewing Customers: Analysis of the Variable PORCE

A total of 14,040 data records in the file CARTERA261303.xls were received from FinComun\textsuperscript{14}.

A total of 390 data records were discarded because there were data entries for historical credits but no historical transaction code (NOBPKS). A listing of these records was saved in the file REJECTED_RECORDS.xls.

A total of 3,737 records were omitted because there was only one historical credit. This was done because it was reasoned that in these cases the final outcome of the current credit was not yet known and therefore the sequence of past behavior leading to present behavior was incomplete. A listing of these omitted records was saved in the file RENEWING_CLIENTS_OMITTED_RECORDS.xls.

The remaining 9,910 records were divided into three “history groups” designated HP2 (History PORCE, 2 credits) through HP4.

- HP2: 2,615 records of customers with two historical credits.
- HP3: 2,185 records of customers with three historical credits
- HP4: 5,110 records of customers with at least four historical credits

Within each individual record, the risk behavior of the customer for a given credit was scored on the basis of the value of the variable PORCE; that is, the percent of payments in a credit that were late. If the value of PORCE was greater than a user defined value then the credit was scored as being “late”; similarly, if the value of PORCE was less than or equal to the same user defined value then the credit was scored as being “on time”.

\textsuperscript{14} All files referred to in the text are provided on duplicate CD’s.
Customers were then scored and divided into “behavior groups” on the basis of their sequence of late and on time behavior. For example, within the history group of customers with two credits (HP2) there are a total of four different sequences of risk behavior and therefore there are four different behavior groups.

- on time credit 1 and on time credit 2
- on time credit 1 and late credit 2
- late credit 1 and on time credit 2
- late credit 1 and late credit 2

Within a given history group the proportion of customers belonging to each possible behavior group was calculated. A “behavior path tree” was then constructed to represent each of the 16 possible behavior paths that could be followed for a customer with four credits. At each possible branch point in the behavior path tree the average proportion and standard deviation on the proportion of customers who, given their past behavior, would fall on the late or on time branches was noted.\(^\text{15}\)

Data Manipulations for Predicting Risk Behavior of Renewing Customers: Analysis of the Variable MORA+ALTA

The original set of 14,040 records in the file CARTERA261303.xls was sorted by maturity date of the current credit. A total of 2,242 records with maturity date of most recent credit earlier than 1-Jan-03 were discarded.\(^\text{16}\)

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\(^{15}\) It was possible to calculate averages and standard deviations because of the construction of history groups. For example, for each history group the behavior on the first recorded credit was scored and then average and standard deviations across history groups was calculated. Note, then, that there is no defined average or standard deviation for the behaviors on the fourth credit because only data from one history group (HP4) was available.

\(^{16}\) The sorting and selection procedures for the data that were used for the MORA+ALTA analysis were different than those used in the FORCE analysis. For the FORCE analysis, which was performed first, the
The remaining 11,798 records were sorted into five “history groups” designated HMA0 (History MORA+ALTA, zero historical credits) through HMA4.

- HMA0: 206 records of customers with only a current credit
- HMA1: 2,921 records of customers with a current credit and one historical credit
- HMA2: 2,154 records of customers with a current credit and two historical credits
- HMA3: 1,869 records of customers with a current credit and three historical credits
- HMA4: 4,648 records of customers with a current credit and four historical credits

Within each individual record, the risk behavior of the customer in a given credit was scored on the basis of the value of the variable PORCE; that is, the percent of payments in a credit that were late. If the value of PORCE was greater than a user defined value then the credit was scored as being late; similarly, if the value of PORCE was less than or equal to the same user defined value then the credit was scored as being on time.

The average and standard deviations of the variable MORA+ALTA – the most number of weeks that a late payment was in arrears - were calculated:

- for all late first credits across HMA1 through HMA4
- for all late second credits across HMA2 though HMA4
- for all late third credits across HMA3 and HMA4
- and for all late fourth credits across HMA4

emphasized of the sorting and selection procedures was on discarding records that might have inaccurate, or incomplete, entries for the sequence of behavior on historical credits. The MORA+ALTA analysis was conducted as a supplement to the screening of customers for their eligibility for a home improvement loan; for this purpose, past credit history was not directly relevant but whether or not the customer could be considered current was directly relevant.
The calculated averages and standard deviations were noted on the behavior path tree\textsuperscript{17}.

\textbf{Data Manipulations for Predicting Risk Behavior of Renewing Customers: Analysis of Defaults}

A total of 471 unique records of defaulted credits in the file ESTADO3.xls were received from FinComun. Records of past credits of these defaulting clients in the file HISTORIA DE CREDITOS ESTADO3.xls were also received.

Historical records for credits older than n-4, where n represented sequential number of the defaulting credit, were discarded. The remaining records were sorted into four groups designated HDF0 (History defaults, zero historical records) through HDF3.

- HDF0: 276 records of customers with a defaulting credit and zero historical credits
- HDF1: 89 records of customers with a defaulting credit and one historical credit
- HDF2: 40 records of customers with a defaulting credit and two historical credits
- HDF3: 66 records of customers with a defaulting credit and three historical credits

Within each individual record, the risk behavior of the customer for a given credit was scored on the basis of the value of the variable PORCE; that is, the percent of payments in a credit that were late. If the value of PORCE was greater than a user defined value then the credit was scored as being “late”; similarly, if the value of PORCE was less than or equal to the same user defined value then the credit was scored as being “on time”.

Customers were then scored and divided into “behavior groups” on the basis of their sequence of late and on time behavior. For example, within the history group of

\textsuperscript{17} Note that the averages and standard deviations for MORA+ALTA are for \textit{all} credits of a given position within a sequence of credits \textit{independent} of the late or on time status of previous credits.
defaulting customers with two historical credits (HDF2) there are a total of four different sequences of risk behavior and therefore there are four different behavior groups.

- on time credit 1 and one time credit 2 and defaulting credit 3
- on time credit 1 and late credit 2 and defaulting credit 3
- late credit 1 and on time credit 2 and defaulting credit 3
- late credit 1 and late credit 2 and defaulting credit 3

Within a given history group the proportion of customers belonging to each possible behavior group was calculated.

**Data Manipulations for Predicting Risk Behavior of New Customers: Analysis of the Variable LIQSUGER**

The history group HMA0 – 206 customers with only a current credit – was reduced by discarding customers whose current credit had a term in excess of 16 weeks. The remaining 175 records were sorted and grouped according to the value of the variable LIQSUGER (suggested liquidity index for current credit)\(^\text{18}\). Records were grouped by 0.1 intervals of LIQSUGER beginning with 1.7 and were centered at the approximate midpoint of the interval. For example, if the value of LIQSUGER was 1.73 then this record was grouped together with other records having values of LIQSUGER ranging from 1.70 to 1.79 and the entire group was centered at 1.75. The centered values of the LIQSUGER intervals were given the variable designation LIQSUGER\_GROUP.

Within each individual record, the risk behavior of the customer in a given credit was scored on the basis of the value of the variable PORCE; that is, the percent of payments in a credit that were late. If the value of PORCE was greater than the user

\(^{18}\) This variable is effectively the ratio of the total weekly income of the client less weekly expenses to the proposed weekly payment; *i.e.*, free cash flow.
defined value then the credit was scored as being "late"; similarly, if the value of PORCE was less than or equal to the same user defined value then the credit was scored as being "on time". 

For each value of LIQSUGER_GROUP the proportion of records for which payments were "late" was calculated, this variable was designated PROBABILITY_LATE_PAYMENTS. Groupings with less than three records were discarded\(^{19}\) and records with values of LIQSUGER_GROUP in excess of 2.99 were discarded\(^{20}\). A total of 109 records remained.

Ordinary least squares estimates of the parameters in a model for the prediction of the probability of late payments - equation 1 - were performed using the statistical package EVViews4.1.

(Equation 1) \[ \text{PROBABILITY}_\text{LATE}_\text{PAYMENTS} = \beta_1 + \beta_2 (\text{LIQSUGER}_\text{GROUP}) + \epsilon \]

The variable LIQSUGER_GROUP was weighted by the number of observations in the group by the simple device of repeating the observed value for a given LIQSUGER_GROUP data point by a number of times equal to the number records that comprised the group. For example, the LIQSUGER group centered on 1.75 and ranging from 1.70 to 1.79, there were four records and in each of these records the customers had at least one late payment; therefore, for the regression to estimate parameters for at least one late payment four "observations" of (1.75, 100%) were included.

\(^{19}\) This elimination increased the "granularity" of the data; in other words, the proportion of records for which payment was "late" for a two record group could only be 0%, 50% or 100% (low granularity); while, for a three record group the proportions could be 0%, 33%, 66% or 100% (higher granularity). 

\(^{20}\) This elimination was undertaken because there was no clear pattern of behavior for customers with liquidity indices of 3.0 and above. Customers with liquidity indices in this range did, on occasion, exhibit bad credit behavior but presumably for reasons substantially other than low cash flow. Roughly 60% of the new customer data set had liquidity indices less than 2.99.
Gender Differences

Analyses of renewing client risk behaviors were conducted as described above for male and female clients together. Records were then scored for gender of the client by identifying male and female names. A total of 51 records were discarded at this point because the name of the client was missing, ambiguous, or obscure. Renewing client risk behaviors were then recalculated for males and females separately.
Results

Predicting Risk Behavior: New Clients

Ordinary least squares parameter estimates in a linear model for the prediction of the risk behavior of new customers — equation 1 - are shown in Table I. The model is saved in the file NEW_CREDIT_RISK_MODEL.xls.

(Equation 1) \[ \text{PROBABILITY\_LATE\_PAYMENTS} = \beta_1 + \beta_2(\text{LIQ\_SUGER\_GROUP}) + \varepsilon \]

Table I. Ordinary least squares parameter estimates for the prediction of the likelihood of late payments. In all cases shown, the estimates are highly significant - T statistic >> 2.0 - meaning that there is more than 95% confidence that the true value of the parameter is not zero (if the parameter were zero then there would be no predictive power).

<table>
<thead>
<tr>
<th>Number of Late Payments</th>
<th>$R^2$ (percent of variance explained)</th>
<th>Parameter</th>
<th>Value</th>
<th>T-statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>&gt;0</td>
<td>80%</td>
<td>$\beta_1$</td>
<td>1.73</td>
<td>32.2</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$\beta_2$</td>
<td>-0.47</td>
<td>-20.4</td>
</tr>
<tr>
<td>&gt;1</td>
<td>80%</td>
<td>$\beta_1$</td>
<td>1.93</td>
<td>27.1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$\beta_2$</td>
<td>-0.62</td>
<td>-20.3</td>
</tr>
<tr>
<td>&gt;2</td>
<td>43%</td>
<td>$\beta_1$</td>
<td>1.23</td>
<td>12.8</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$\beta_2$</td>
<td>-0.37</td>
<td>-9.0</td>
</tr>
</tbody>
</table>

The models appear to be very good predictors of the probability that a new customer with liquidity index less than 3.0 will have more than zero or more than one late payment; the model for prediction of more than two late payments is less robust but still reasonable. A graphical representation of these models is shown in Figure 2.
Figure 2. Probabilities of late payments. Symbols represent actual observations, lines represent predictions.

Predicting Risk Behavior: Renewing Clients

An active Microsoft® Excel 2002 spreadsheet tool containing the “behavior path tree” for renewing customers was created as the file RENEWING_CREDIT_RISK_TOOL.xls. The user defined input into the tool is a value against which the variable PORCE is compared for each credit within a record. If the value of PORCE is greater than the user defined input value then the credit is scored as being “late”; similarly, if the value of PORCE is less than or equal to the same user defined input value then the credit is scored as being “on time”.

Using the tool, it was found that the incidence of late payments on a credit increases with past incidences of late payments on credits; in other words, customers who make late payments on a credit are more likely to make late payments on their next credit
than are customers who make on time payments. This relationship holds regardless of how many late payments are used to define “late”. Three example outputs from the tool are shown in Figure 3.

**Figure 3.** Late payment behavior: probabilities of successive credits with late payments. Three different definitions of “late”: at least one late payment in 16 (6%), at least two late payments in 16 (13%), at least three late payments in 16 (19%).

Using the tool, it was also found that, when late, customers tended to be in arrears for longer periods of time when they had a longer history of credits. This relationship holds regardless of how many late payments are used to define “late”. Three example outputs from the tool are shown in Figure 4.

Full “behavior path tree” outputs from the tool for definitions of “late” ranging from at least one late payment in 16 to at least four late payments in 16 are included in Appendix A.
Figure 4. Late payment behavior: average number of weeks in arrears on successive credits. Three different definitions of “late”: at least one late payment in 16 (6%), at least two late payments in 16 (13%), at least three late payments in 16 (19%).

In general, regardless of the definition of “late”, defaulting clients are substantially more likely to have been “late” on previous credits than non-defaulting clients (Table II). In the minimum case defaulting clients with only one previous credit were 1.57 times more likely to have had at least one late payment in the previous credit than non-defaulting clients.

Table II. Incidences of previous late payments among defaulting and non-defaulting clients.

<table>
<thead>
<tr>
<th>Definition of &quot;late&quot;: minimum number of late payments in 16</th>
<th>Proportion of non-defaulting clients who are &quot;late&quot;</th>
<th>Proportion of defaulting clients who are &quot;late&quot;</th>
<th>Average Relative Likelihood that defaulting clients have previous &quot;late&quot; credits</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 previous credit</td>
<td>1 previous credit</td>
<td>2 previous credits</td>
<td>3 previous credits</td>
</tr>
<tr>
<td>1</td>
<td>50%</td>
<td>78%</td>
<td>69%</td>
</tr>
<tr>
<td>2</td>
<td>29%</td>
<td>63%</td>
<td>38%</td>
</tr>
<tr>
<td>3</td>
<td>16%</td>
<td>53%</td>
<td>23%</td>
</tr>
<tr>
<td>4</td>
<td>11%</td>
<td>42%</td>
<td>15%</td>
</tr>
</tbody>
</table>
In general, males exhibited riskier patterns of credit behavior than females. Full “behavior path tree” outputs from the tool for definitions of “late” ranging from at least one late payment in 16 to at least four late payments in 16 for males are shown in Appendix B and for females are shown in Appendix C. This difference was, however, not extreme (Tables III & IV).

Table III. Credit risk behavior of male clients with one previous credit relative to all clients.

<table>
<thead>
<tr>
<th>Definition of &quot;late&quot;: minimum number of late payments in 16</th>
<th>All Clients</th>
<th>Males</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Non-defaulters</td>
<td>Defaults</td>
</tr>
<tr>
<td>1</td>
<td>50%</td>
<td>78%</td>
</tr>
<tr>
<td>2</td>
<td>29%</td>
<td>63%</td>
</tr>
<tr>
<td>3</td>
<td>16%</td>
<td>53%</td>
</tr>
<tr>
<td>4</td>
<td>11%</td>
<td>42%</td>
</tr>
</tbody>
</table>

Table IV. Credit risk behavior of male clients with three previous credits relative to all clients.

<table>
<thead>
<tr>
<th>Definition of &quot;late&quot;: minimum number of late payments in 16</th>
<th>All Clients</th>
<th>Males</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Non-defaulters</td>
<td>Defaults</td>
</tr>
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<td>1</td>
<td>20%</td>
<td>37%</td>
</tr>
<tr>
<td>2</td>
<td>7%</td>
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</tr>
<tr>
<td>3</td>
<td>2%</td>
<td>7%</td>
</tr>
<tr>
<td>4</td>
<td>0.9%</td>
<td>7%</td>
</tr>
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</table>
Discussion

The present work illustrates one possible technique for improving the management of credit risks in microfinance.

The risk of late payments by new microborrowers can be predicted from their current free cash flow. Free cash flow represents a measure of the capacity of the microborrower to make repayments from his or her current income. That low free cash flows result in a higher frequency of late payments makes intuitive sense. At a deeper level, however, it may indicate that such clients also have relatively restricted access to the informal credit market; that is, they cannot finance their payments through moneylenders or family and friends.

The risk of late payments and maximum number of weeks in arrears by renewing microborrowers can be predicted from their past incidences of late payments. This finding supports the theoretical notion of Amendariz de Aghion & Morduch (2000) that frequent payments carry valuable information for microlenders and that this information can be used to mitigate credit risks.

To the extent that this work has shown that the credit risk behavior of FinComun’s clients is predictable it has also therefore demonstrated that credit risk is to an equal extent, manageable. The prescription of techniques for managing elevated credit risks are, emphatically, not within the scope of this work. More particularly, the emphasis on the prediction of risky credit behavior is certainly not meant to imply that a punitive approach to managing credit risks is desirable. Rather, the tools developed allow the management and staff of FinComun to make more informed decisions about what kinds of extraordinary interventions, if any, may be warranted in the event of risky
credit behavior by clients. Indeed, the tools permit the definition of risky credit behavior to be varied and selected.

An underlying theme of this work has been that individual microborrowers deserved to be evaluated on the basis of their behavior and not on the basis of some descriptive attribute. Indeed designation of potential microborrowers as “poor” contributed to the historical dearth of formal credit facilities serving the neediest among us. Nevertheless, a strong theme in microfinance has been that females are better credit risks than males; additionally, there is a theme that the social value of enhancing the well being of females is greater than the social value of enhancing the well being of males. In this work, and in confirmation of the theme of gender differences, males were found to exhibit riskier credit behavior than females. However, except for the most extreme forms of risky behavior – for example, holding three microcredits in a row, and being late with at least 25% of payments on each of these microcredits, and then defaulting on the fourth microcredit – the relative likelihoods for males to exhibit riskier credit behavior than gender undifferentiated clients were less than 1.10. Furthermore, percent increases in maximum number of weeks in arrears, if late, relative to all clients were generally less than 2%.

To the extent that management of credit risks at FinComun is enhanced by the use of the tools developed in this work then it is to be expected that overall program efficiency would be improved. This can only enhance the social effectiveness of the program: at a minimum, the improved efficiency will result in savings which could be redeployed for additional microcredits.
References


## Appendix A. Behavior Path Trees, All Clients

<table>
<thead>
<tr>
<th>Credit 1</th>
<th>M^a = 1.20 1.02</th>
<th>Late</th>
<th>On time</th>
<th>&quot;Late&quot; &gt; 0.047</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Late</td>
<td>On time</td>
<td>Late</td>
</tr>
<tr>
<td>0</td>
<td></td>
<td>50%</td>
<td>50%</td>
<td>On time</td>
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<tr>
<td>0.047</td>
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</table>

<table>
<thead>
<tr>
<th>Credit 3</th>
<th>M^a = 1.23 0.87</th>
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<th>On time</th>
<th>&quot;Late&quot; &gt; 0.009</th>
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<tbody>
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<td></td>
<td></td>
<td>Late</td>
<td>On time</td>
<td>Late</td>
</tr>
<tr>
<td>0</td>
<td></td>
<td>38%</td>
<td>35%</td>
<td>Off time</td>
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<td>0.009</td>
<td></td>
<td></td>
<td></td>
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<table>
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<tr>
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<th>Late</th>
<th>On time</th>
<th>&quot;Late&quot; &gt; 0.016</th>
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<td>On time</td>
<td>On time</td>
<td>Late</td>
</tr>
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<td>0</td>
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<td>60%</td>
<td>39%</td>
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<td>0.016</td>
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</table>

<table>
<thead>
<tr>
<th></th>
<th></th>
<th>&quot;Late&quot; &gt; 0.021</th>
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</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>On time</td>
</tr>
<tr>
<td>0.021</td>
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<td>Off time</td>
</tr>
<tr>
<td>0.021</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Credit 1</td>
<td>Credit 2</td>
<td>Credit 3</td>
</tr>
<tr>
<td>---------</td>
<td>----------</td>
<td>----------</td>
</tr>
<tr>
<td>MA= 1.56 1.33</td>
<td>MA= 1.67 1.38</td>
<td>MA= 1.67 1.38</td>
</tr>
<tr>
<td>Late</td>
<td>34% 0.032</td>
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<tr>
<td>On time</td>
<td>66% 0.032</td>
<td>On time</td>
</tr>
<tr>
<td>Late</td>
<td>24% 0.039</td>
<td>Late</td>
</tr>
<tr>
<td>On time</td>
<td>76% 0.088</td>
<td>On time</td>
</tr>
<tr>
<td>Late</td>
<td>48% 0.039</td>
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</tr>
<tr>
<td>On time</td>
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</tr>
<tr>
<td>Late</td>
<td>13% 0.042</td>
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<tr>
<td>On time</td>
<td>87% 0.042</td>
<td>On time</td>
</tr>
<tr>
<td>Late</td>
<td>32% 0.039</td>
<td>Late</td>
</tr>
<tr>
<td>On time</td>
<td>68% 0.039</td>
<td>On time</td>
</tr>
<tr>
<td>Late</td>
<td>27% 0.042</td>
<td>Late</td>
</tr>
<tr>
<td>On time</td>
<td>73% 0.042</td>
<td>On time</td>
</tr>
<tr>
<td>Late</td>
<td>22% 0.039</td>
<td>Late</td>
</tr>
<tr>
<td>On time</td>
<td>78% 0.039</td>
<td>On time</td>
</tr>
</tbody>
</table>

Note: MA = Mean of the absolute value of the deviation from the mean.
<table>
<thead>
<tr>
<th>Credit 1</th>
<th>Credit 2</th>
<th>Credit 3</th>
<th>Credit 4</th>
<th>Credit 5</th>
<th>Credit 6</th>
<th>Credit 7</th>
<th>Credit 8</th>
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<tbody>
<tr>
<td>MA= 1.57</td>
<td>MA= 1.72</td>
<td>MA= 1.45</td>
<td>MA= 1.40</td>
<td>MA= 1.45</td>
<td>MA= 1.45</td>
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<tr>
<td>Late</td>
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<td>3%</td>
<td>31%</td>
<td>32%</td>
<td>33%</td>
<td>33%</td>
<td>34%</td>
</tr>
<tr>
<td>On time</td>
<td>66%</td>
<td>97%</td>
<td>69%</td>
<td>68%</td>
<td>67%</td>
<td>67%</td>
<td>66%</td>
</tr>
<tr>
<td>Late</td>
<td>26%</td>
<td>3%</td>
<td>31%</td>
<td>32%</td>
<td>33%</td>
<td>33%</td>
<td>34%</td>
</tr>
<tr>
<td>On time</td>
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<td>68%</td>
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<td>67%</td>
<td>66%</td>
</tr>
<tr>
<td>Late</td>
<td>37%</td>
<td>3%</td>
<td>31%</td>
<td>32%</td>
<td>33%</td>
<td>33%</td>
<td>34%</td>
</tr>
<tr>
<td>On time</td>
<td>63%</td>
<td>97%</td>
<td>69%</td>
<td>68%</td>
<td>67%</td>
<td>67%</td>
<td>66%</td>
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<tr>
<td>Late</td>
<td>14%</td>
<td>3%</td>
<td>31%</td>
<td>32%</td>
<td>33%</td>
<td>33%</td>
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<tr>
<td>On time</td>
<td>86%</td>
<td>97%</td>
<td>69%</td>
<td>68%</td>
<td>67%</td>
<td>67%</td>
<td>66%</td>
</tr>
</tbody>
</table>

"Late" >= 13% of payments
"Late" >= 19 % of payments

Credit 1
MA = 1.83 1.52

Credit 3
MA = 1.93 1.64

Late 29% 0.021
On time 71% 0.021

Late 20% 0.090
On time 80% 0.090

Late 28% 0.081
On time 72% 0.081

Late 11% 0.034
On time 89% 0.034

Appendix B. Behavior Path Trees, Male Clients
<table>
<thead>
<tr>
<th>Credit 1</th>
<th>Credit 2</th>
<th>Credit 3</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>MA</strong></td>
<td><strong>MA</strong></td>
<td><strong>MA</strong></td>
</tr>
<tr>
<td>2.24</td>
<td>2.22</td>
<td>2.84</td>
</tr>
</tbody>
</table>

### Late Payments

- **Late** 28% 0.036
- **Late** 10% 0.014
- **Late** 18% 0.050
- **Late** 8% 0.030

### On-Time Payments

- **On time** 73% 0.036
- **On time** 90% 0.014
- **On time** 84% 0.080
- **On time** 92% 0.030

### Probability Matrix

<table>
<thead>
<tr>
<th></th>
<th>Credit 1</th>
<th>Credit 2</th>
<th>Credit 3</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Late</strong></td>
<td>0.036</td>
<td>0.014</td>
<td>0.050</td>
</tr>
<tr>
<td><strong>On time</strong></td>
<td>0.036</td>
<td>0.014</td>
<td>0.080</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>0.036</td>
<td>0.014</td>
<td>0.080</td>
</tr>
</tbody>
</table>

---

Appendix B: Behavior Path Trees: Male Clients
"Late" >= 6% of payments

Credit 1
MA = 1.35 1.35

Late 28% 0.052
On time 72% 0.052

Credit 3
MA = 1.36 1.02

Late 49% 0.002
On time 51% 0.002

Late 29% 0.031
On time 71% 0.031

Late 44% 0.076
On time 56% 0.076

Late 17% 0.008
On time 83% 0.008
### Credit 1

MA = 1.56 1.38

- **Late**: 15% 0.037
- **On time**: 85% 0.037

### Credit 2

MA = 1.63 1.32

### Credit 3

MA = 1.54 1.27

<table>
<thead>
<tr>
<th></th>
<th>% of Payments</th>
<th>Probability</th>
</tr>
</thead>
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</tr>
<tr>
<td>On time</td>
<td>66% 0.019</td>
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<td>Late</td>
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<tr>
<td>On time</td>
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<tr>
<td>Late</td>
<td>27% 0.030</td>
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<tr>
<td>On time</td>
<td>73% 0.030</td>
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<tr>
<td>Late</td>
<td>12% 0.036</td>
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</tr>
<tr>
<td>On time</td>
<td>88% 0.036</td>
<td></td>
</tr>
</tbody>
</table>
### Credit 1

- **MA**: 1.75
- **Late**: 19% of payments

### Credit 3

- **MA**: 1.88
- **Late**: 27% of payments
- **On time**: 73% of payments

### Credit 2

- **MA**: 1.58
- **Late**: 16% of payments
- **On time**: 84% of payments

### Credit 4

- **Late**: 11% of payments
- **On time**: 89% of payments

### Credit 5

- **Late**: 9% of payments
- **On time**: 91% of payments