

Default Risk Modelling in Credit Cards – A Study of Merchant and Acquiring Bank Relationship

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ABSTRACT

A globally integrated business environment presents a host of expansion opportunities to the banks, particularly related to credit cards business. These opportunities, however, have risk attached to them. This risk is present in all possible forms: operational risk, financial risk, country risk, etc. Financial risk has a unique nature of being ‘invisible’ at a given point in time. It usually occurs in the future. Hence, it becomes necessary to foresee and predict it. Moreover, in credit cards’ business, financial risk is inherent in the core operations. Banks, in the credit card business, face financial risk in the form of both credit risk and fraud risk. Both of these can be caused by either the card holders or the merchants. In this paper, we have focused on a very specific aspect of the financial risk, known as the credit default risk, posed by the merchants to their respective acquiring banks. We have created a data-driven solution, which explains the relationship between the merchants and their acquiring banks from a credit risk perspective and acts as an “early warning” system for the management. Our solution is based on a logistic regression model, developed using a statistical package called Statistical Analysis System (SAS) This model assesses the merchant portfolio of the acquiring bank and assigns a “probability score” of default (PD) to each merchant. Such a score warns the management in advance of probable future losses on merchant accounts. Banks can rank order merchants based on their PD score, and instead of working on the entire merchant portfolio, they can focus on the relatively riskier set of merchants.

KEYWORDS: Merchant risk; Acquiring bank; Risk management; Risk; Credit risk management; Logistic regression; SAS

JEL Classification: G32

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INTRODUCTION

The merchant-acquirer relationship is often ignored by the banks when planning for risk management. The relationship, however, poses an “invisible” risk to the acquiring banks because, when a transaction is recorded at a merchant today, the risk from this transaction arises a few months into the future. This makes the risk unforeseeable. The motivation behind this paper is to

create an “early warning” system to tackle the above-mentioned challenge posed by the merchant-acquirer relationship. This early warning system enables the banks to estimate the expected loss from the defaults predicted by the model and strategise accordingly. Such an early warning system is possible to create because of the availability of live transactional data with the banks. These data can be leveraged by using tools like

SAS and *Structured Query Language* (SQL). Server to derive analytical insights and then create a statistical model. This model can then be run on live data.

MERCHANT-ACQUIRER RELATIONSHIP: BUSINESS FRAMEWORK

Merchants, who accept credit cards, get a point of sale (POS) device installed at their outlet. This POS device is installed through a bank, and this bank is known as the acquiring bank or simply the acquirer. When a transaction is recorded by a merchant, a copy of the receipt signed by the customer is sent to the bank by the merchant for claiming the amount of transaction. The acquiring bank settles this within a stipulated number of days, after deducting a surcharge, known as discount rate.

Figure 1 given below shows the flow of events once a transaction is done by a customer at a merchant. The merchant sends a copy of the signed receipt to the acquiring bank. The bank, in turn, settles the dues to the merchant and also communicates the transaction details to the customer bank, via the credit card association. Once this communication is received by the customer bank, it adds this transaction to the customer’s statement of account.

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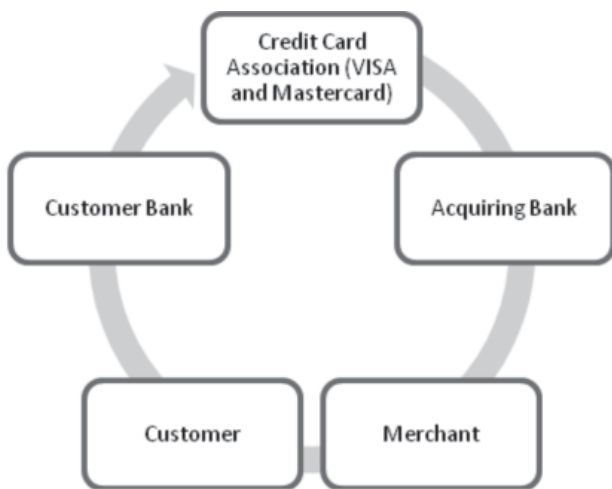


Figure 1: A typical credit card business model

MERCHANT-ACQUIRER RELATIONSHIP: CREDIT RISK

According to the Basel Committee on Banking Supervision, “Credit risk is the potential that a counter party fails to meet the obligations on agreed terms”. We will now discuss the cause of credit risk in the merchant-acquirer relationship.

In such a relationship, credit risk is imposed primarily by the disputes raised by the customers against the merchants. Any situation, where payment is made in advance and the delivery of service/product happens in future (for example airlines, home furnishings, etc.), could lead to a dispute between the customer and the merchant, and hence poses a credit risk to the acquiring bank from the merchant side.

To understand this in detail, we take an example of a retail merchant. When a customer purchases grocery from a retail store and her credit card is swiped for payment, the transaction is recorded and a transaction slip is generated by the POS device, which is signed by the customer. At the end of the day, the merchant sends this transaction slip to the acquiring bank for claiming the transaction amount. This amount is reimbursed to the merchant within a few days, as mentioned in the merchant-acquirer contract.

However, the possibility of risk arises when a customer receives the monthly credit card statement and finds out that the amount that was charged from her is more than what she had shopped for. This is when the customer raises a dispute with her bank, highlighting the “invalid” charges in her account statement. The bank issues a temporary credit to the customer and initiates the dispute investigation process. The issue here is that, by the time the customer has raised a dispute, the merchant would have received the payment from the acquiring bank. If the dispute investigation process is resolved in favour of the customer, then the

same is communicated by the customer’s bank to the acquiring bank and, in such a case, the merchant owes the money back to its acquiring bank. This process is explained below in the Figure 2.

In such a situation, the merchant is said to be in “debit balance”. Once a merchant is in debit balance in the books of acquiring bank, he is given a stipulated period of time to payback the amount due. Once this time window expires and the merchant has not yet paid the amount, then next day onwards the merchant is considered to be “1 dpd” (one day past due). Till the time the merchant does not pay back, he ages in the dpd window. If the merchant is 90 dpd for more than a fixed amount of money, he is tagged as a “default” merchant (*Braun et al., 2008*).

Default rate of the merchant portfolio is defined as the ratio of the number of default merchants and the number of merchants in the portfolio (*Hansen et al., 1996*).

CREDIT RISK MODELLING IN MERCHANT-ACQUIRER RELATIONSHIP: THE NEED

An acquiring bank can have millions of merchants in its global portfolio. While all merchants would be risky at some level, all of them do not pose the same credit risk. The management of the bank cannot build risk management strategy for the entire merchant portfolio. Hence, it would be helpful for the bank if they can assign a “probability of default” (PD) score to the merchants based on the level of risk posed by them and then sort the list of merchants in the decreasing order of this probability score. We propose to build a statistical model, which would help the acquiring bank in the following ways:

1. The model will generate PD scores for all the merchants in the portfolio of the bank. This would help the bank in identifying the high-risk merchants and plan accordingly.

2. The model will act as an “early warning” system, which will give the acquiring bank some visibility into the potentially “invisible” credit risk in the future.

The above-mentioned points enable the banks to create sufficient reserves in advance, in view of the credit risk they foresee using the model. Also, the banks can do further analysis on the kind of industries, geographies, etc. that are posing more risk and plan accordingly.

CREDIT RISK MODELLING: METHODOLOGY

As discussed earlier, the number of merchants in the global portfolio of the bank can be in millions. This creates a need for a statistical model. However, to make an effective model, we propose to first create segments of merchants based on their perceived risk profile and then create the required models for each of the segments. The methodology is described in detail below:

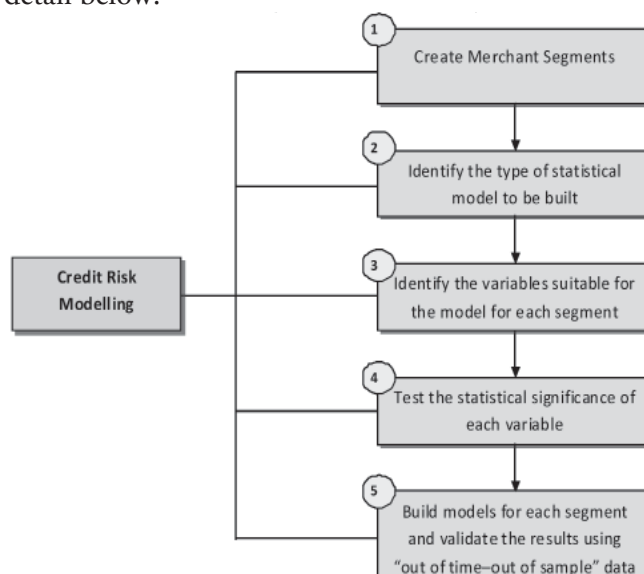


Figure 2: Credit risk modelling

1. *Create merchant segments*: Figure 3 shows the merchant segments based on two attributes, namely, the ability to pay and the willingness to pay. Merchants who are high on both these

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attributes are least risky and a credit risk model may not be required for them. Merchants who are low on willingness to pay are generally risky group of merchants.

		Willingness to pay	
		High	Low
Ability to pay	High	Lowest Risk	High Risk
	Low	Lower Risk	Highest Risk

Figure 3: Merchant segmentation framework

A point to understand is that, while this classification is subjective in nature to some extent, at the same time, it is not critical to get this classification absolutely right. This framework is more of a guiding tool, and even if some merchants do get misclassified, it does not impact the model because in the end all the merchants are risky and the models can be built for all the four segments above. In this paper, we have built the credit risk model on merchants who have high ability and low willingness to pay, highlighted in light red colour in the Figure 3.

2. Identify the type of statistical model to be built:

In the credit risk model that we have built, the dependent variable is “whether a merchant will go into default or not”. This is a binary variable, with the value “1” representing that the merchant will go into default and the value “0” representing that the merchant will not go into default. Hence, we have used logistic regression to model the risk.

Another choice that we had to make was based on the nature of the model required. Broadly speaking there are two types of models: *Transaction level* and *Account level*. The transaction-level model gets triggered when the transaction is recorded at a merchant and uses the transaction variables. The drawback of this model is that if a merchant does not have too many transactions (on analysis of data, it was observed that 90% of the merchants in the sample data had more than 100 transactions per day on an average. Therefore, a minimum of 100 transactions per day were considered

as being sufficient to build a statistical model) or has seasonal transactions, then this model may not be useful, because there will not be enough transactions to get a reliable PD score.

To overcome this, one can use the account-level model, which uses variables that are merchant specific, irrespective of whether a transaction is being recorded at the merchant or not. However, the drawback of this model is that the variables are not updated because they are based on merchant history rather than on fresh transactions. In this paper, we have built a transaction-level model, to demonstrate its usefulness.

3. *Identify suitable variables*: Suitable variables for each segment need to be identified by combining business experience of the management supported by statistical significance of the variable itself. Another thing that needs to be taken care of is the sign of the variable. The variable needs to have predictive power, but in the right direction.

MODELLING FRAMEWORK

This includes the time period for historical data that will be used in developing the model. For validation of the model, we need to create ‘out of time-out of sample’ dataset. In this paper, we have used the following timeframes:

- Model development dataset*: It is based on the time period from January 2008 to December 2008. The time period chosen is 1 year, assuming that most banks do not store data that is older than 1 year because of the enormity of data and costs associated with storage.
- Model validation dataset*: It begins from January 2009 and ends in December 2009, on a different sample of merchants.

CREDIT RISK PD MODEL DEVELOPMENT

We have proposed a credit risk PD model to assess the risk associated with the merchant-acquirer relationship

from an acquirer’s perspective. As discussed, we have chosen the logistic regression technique to build the model. Subsequently, we have tested the model on “out of time-out of sample” data.

Table 1 shows the summary of the model prerequisites that we have used.

Table 1: Summary of modelling framework

Default definition	A merchant is tagged as default if he is 90 dpd for more than \$100.
Regression technique	Logistic regression
Timeframe	Development dataset: January 2008 – December 2008 Validation dataset: January 2009 – December 2009
Modelling platform	SAS, SQL Server
Model type	Transaction-level model
Merchant segment	High risk (high willingness and high ability to pay)

Sample of transaction-level data

The below-mentioned Table 2 is only a snapshot of transaction-level data. We have not shown the exhaustive list of variables, which usually are hundreds in number. Here, we have shown the variables finally used in the model.

Table 2: Variables used in the PD model

Merchant_ID	Trans_dt	Sub_dt	Trans_amt	No_of transact_last 5days	No_of_cus_t_last 5days	No_of_disputes
9100011001	20/2/2008	24/2/2008	167	5625	2345	12
9100011002	10/3/2008	13/2/2008	234	6085	3567	14
9100011003	11/5/2008	13/5/2008	556	4087	3875	13
9100011004	21/6/2008	25/6/2008	1340	15000	8776	15
9100011003	23/1/2008	27/1/2008	406	20980	12376	13
9100011002	25/7/2008	28/7/2008	667	16076	9876	14
9100011001	28/8/2008	1/9/2008	300	20034	12345	12
9100011004	7/9/2008	11/9/2008	224	8576	4678	15
9100011003	8/10/2008	12/10/2008	856	9957	4567	13
9100011005	10/11/2008	14/11/2008	1070	17876	9876	10

The description of the variables is presented below in the Table 3.

The dispute amount as a variable was also tested for

Table 3: Description of variables used in the PD model

Variable name	Variable description	Variable type
Merchant_Id	A unique identifier for the merchant	Text
Trans_dt	Date of transaction between the merchant and the customer	Date
Sub_dt	Date on which the merchant submits the transaction slip to the acquiring bank	Date
Trans_amt	Transaction amount	Numeric
No_of_disputes	Number of transactions at the merchant disputed by the customers	Numeric
No_of transact_last5days	Number of transactions at the merchant in the last 5 days	Numeric
No_of_cust_last5days	Number of customers transacting at the merchant in the last 5 days	Numeric

significance, and while it was found to be significant, it had high collinearity with other variables, indicating that its presence in the model could inflate the error term in the regression. Hence, this variable was not included in the model. At the same time, this variable could be included in the model, but with the caveat that any bank including this variable in the model should test it across a much larger sample of data to ensure that the influence of this variable is not exaggerated.

After the identification of variables, we applied logistic regression on the framework discussed above. A typical logistic regression model is represented as:

$$z = \beta_0 + \beta_0x_1 + \beta_1x_2 + \beta_2x_3 + \beta_3x_4 \dots\dots\dots 1$$

$$p = 1/(1 + e^{-z})\dots\dots\dots 2$$

Where,

z is the linear function of the dependent variables.

p is the PD that we have modelled.

We have run logistic regression in SAS on the transaction-level data. The SAS output showed the

following values of the β coefficient.

$$\begin{aligned} \beta_0 &= -1.57361219, \\ \beta_1 &= 0.003187, \\ \beta_2 &= 0.00009, \\ \beta_3 &= 0.00023, \\ \beta_4 &= 0.044 \end{aligned}$$

To understand this better, we take an example of a merchant having id 9100011001. For this merchant, the z value comes out to be 0.532217 using equation 5.1.

Using equation 5.2, the PD score of this merchant comes out to be 0.63, which means that this transaction has 63% probability to go into default. Similarly, this model will calculate the PD score of each transaction. Once the PD score is obtained from each transaction, we sort the dataset in descending order of probability score and then consolidate the data into deciles, as shown in the Table 4 below.

Table 4: Percentile distribution of defaults captured by the PD model

Percentile	No. of defaults	Cumulative number of defaults	Percent cumulative number of defaults
10%	689	689	62%
20%	201	890	80%
30%	67	957	86%
40%	46	1003	90%
50%	37	1040	94%
60%	24	1064	96%
70%	17	1081	97%
80%	14	1095	98%
90%	10	1105	99%
100%	7	1112	100%

The graph, known as ROC (receiver operating characteristics) curve, shows that the model captures 63% defaults in the top 10% of transaction data when the data are sorted in decreasing order of the PD score generated by the model. A high percentage of default capture in the top percentile of ROC curve indicates that the model is working as expected and has been

able to fit the data well.

The steepness in the ROC curve indicates the amount by which using a model is better than not using a model at all.

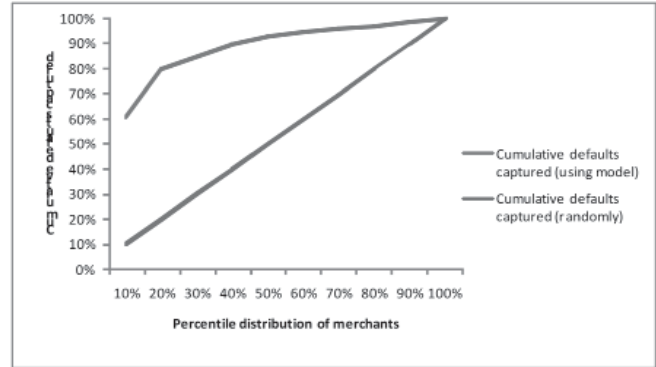


Figure 4: ROC (receiver operating characteristics) curve

The 45° line in Figure 4 indicates the ROC curve when no model is used; hence, each merchant in the portfolio is assumed to have a 50% PD. The area between the actual ROC, originating from the use of the PD model, and the 45° line indicates the incremental benefit emanating from the use of the PD model.

Once the probability score is obtained from each transaction, we sort the dataset in the descending order of the probability score and then consolidate the data into deciles and compare the actual and predicted default rate for each decile, as shown below in the Table 5

Table 5: Comparison of actual default rates and default rates predicted by the PD model

Percentile	No. of defaults	No. of transactions	Actual default rate	Predicted default rate
10%	689	8613	8.00%	7.7%
20%	201	8613	2.33%	2.0%
30%	67	8613	0.78%	1.1%
40%	46	8613	0.53%	0.5%
50%	37	8613	0.43%	0.5%
60%	24	8613	0.28%	0.3%
70%	17	8613	0.20%	0.2%
80%	14	8613	0.16%	0.2%
90%	10	8613	0.12%	0.1%
100%	7	8613	0.08%	0.1%

Actual default rates are calculated as the ratio between the number of defaults in that decile and the total number of merchants in that decile. Predicted default rates are calculated in a similar way, but the numerator in this case represents the total number of merchants tagged as default by the PD model.

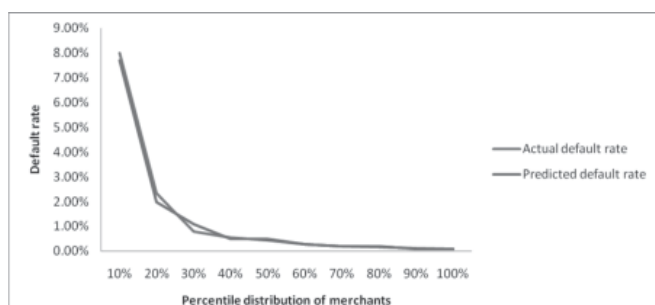


Figure 5: Actual vs predicted comparison for the PD model

Figure 5 shows the comparison of actual default rate and the default rate predicted by the model for each decile and helps us in understanding the model performance in real time.

MANAGERIAL IMPLICATIONS

This research on the credit risk arising from the merchant-acquirer relationship and the subsequent development of the PD model is founded on the concept of risk management. The approach employed to model the credit risk from global credit card operations should be useful for modern day managers of a bank. With the help of the PD model, managers should be able to strategise with the “invisible” credit risk always in their mind.

The PD model will enable the banks to keep in reserve a pool of funds in advance to negate the losses arising from the merchant credit risk. Moreover, managers will find it more efficient to strategise for a smaller set of risky merchants rather than planning for the entire merchant portfolio.

A possible obstacle in the use of this model could be the presence of millions of merchants in a bank’s

portfolio, thereby making the task of classification of these merchants using the merchant segmentation framework very difficult. However, this can be easily overcome by creating geographical portfolios for the merchants instead of taking the entire global merchant base as a whole. As an example, a bank could have 1 million merchants in India, out of which a quarter of a million could be in the northern region. The bank can assess the northern portfolio first and then other regions one by one. Also, banks usually have regional teams that handle merchant relationships in their respective regions. These teams can help in using the merchant segmentation framework.

RESEARCH IMPLICATIONS

The PD model developed in this research study seems to have good explanatory abilities. It is pertinent to mention that the variables used in the PD are not the only set of variables that can be used. The choice of variables would depend on the sample of the data used along with the nature of the data. Hence, it becomes important to test this model under different conditions and in different geographies. Also, it is important to mention that apart from disputes, other causes of credit risk could also be explored.

LIMITATIONS OF THE MODEL AND FUTURE RESEARCH

Although this study has made some contribution towards a better understanding of the risk inherent in a merchant-acquirer relationship, it is not without limitations. The PD model is sensitive to the explanatory variables chosen. It is also dependent, to an extent, on the modelling timeframe chosen, which makes it all the more important to test the model under different set of scenarios and in different economies around the world.

While the PD model can predict the possibility of a merchant going into default, it cannot predict the

amount of default. Since this model is based on logistic regression, the dependent variable needs to be binary in nature. Therefore, to predict the amount of default, the PD model can be extended to another level, where a regression model can be built with the dependent variable being the LGD (loss given default).

While the PD model proposed in this paper is useful for both practitioners as well as researchers, caution needs to be exercised while generalising the findings. In this paper, the PD model was tested on sample data of a bank. Future research attempts should test the generalisability of the PD framework of different banks in different geographies.

CONCLUSION

The management of risk in global business scenario has taken more importance than ever. In the financial services sector, credit risk is inherent in the nature of business. The aim of this research was to create an early warning system for the banks to effectively manage the risk arising out of their merchant-acquirer relationship. To facilitate this, the PD model was proposed. The

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PD model assigns a probability of default to the entire merchant portfolio of the acquiring bank, which can be used by the banks to assess their merchant portfolio more effectively.

In this paper, the business framework of the merchant-acquirer relationship was explained along with the ways in which credit risk can arise from this association. The PD model was created in SAS and applied to the transactional data of a bank. It was observed that the model captured 63% defaults in the top decile of transactions when sorted in the decreasing order of the PD scores.

The PD model was also validated by comparing the actual defaults with those predicted by the model and it was found that there was a very good alignment between the two. This indicated that the model rank ordered the defaults quite close to reality.

To summarise, the PD model is expected to act as a tool for acquiring banks in both analysing as well as strategising for credit risk arising from the merchant side.

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