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Credit risk estimate using internal explicit knowledge

Abstract

Jordanian banks traditionally use a set of indicators, based on their internal explicit knowledge to examine the credit risk caused by default loans of individual borrowers. The banks are reliant on the personal and financial information of the borrowers, obtained by knowing them, often referred as internal explicit knowledge. Internal explicit knowledge characterizes both financial and non-financial indicators of individual borrowers, such as; loan amount, educational level, occupation, income, marital status, age, and gender. The authors studied 2755 default or non-performing personal loan profiles obtained from Jordanian Banks over a period of 1999 to 2014. The results show that low earning unemployed borrowers are very likely to default and contribute to non-performing loans by increasing the chances of credit risk. In addition, it is found that the unmarried, younger borrowers and moderate loan amount increase the probability of non-performing loans. On the contrary, borrowers employed in private sector and at least educated to a degree level are most likely to mitigate the credit risk. The study suggests improving the decision making process of Jordanian banks by making it more quantitative and dependable, instead of using only subjective or judgemental based understanding of borrowers.

Keywords: credit risk, Jordanian banks, default loans, internal explicit knowledge, logistic analysis.
JEL Classification: E51, G32, D81, E47.

Introduction

Banks develop credit strategy to monitor and manage risk associated with default or non-performing personal and enterprise based commercial loans. Typically, banks attempt optimizing returns on their loan portfolios, while minimizing the credit risk, thus ensuring it falls within their specified credit strategy. In particular, the credit risk management aims to maximize a bank's risk-adjusted rate of return by maintaining credit risk exposure within acceptable parameters (Basel, 2013). Credit risk is derived from default receivable, where desired cash flow from loans, securities and derivatives are unclaimed (Saunders and Cornet, 2008). Gup et al. (2007) find credit risk precipitated over a period time leading to systemic banking failures. The Jordanian banking system suffers largely from default or non-performing personal loans, causing unmanageable credit risk. The amount of default or non-performing personal loans of Jordanian banks is much higher compared to international and Arabic banks (Central Bank of Jordan, 2014). In addition, the default retail loan to total loan ratio of Jordanian banks amounts to 11% during year 2008-09 (Central Bank of Jordan, 2010) compared to the Arab world's average of 5.65% over the same period (IMF, 2016). However, the credit risk assessment of Jordanian banks mainly depends on the personal and financial information of the individual borrowers, obtained by knowing them, often referred as internal explicit knowledge. The internal explicit knowledge is the subjective or judgemental understanding of their borrowers. Typically, Jordanian banks compile a set of information and model their credit risk parameters based on internal explicit knowledge.

Several credit risk models, i.e. typically internal credit risk models are developed to quantify risk and estimate credit risk impacts on capital structure of firms (Lopez and Saidenberg, 2000). The main aim of managing credit risk is to maximize a bank's risk-adjusted rate of return by keeping credit risk exposure within acceptable parameters (Lopez and Saidenberg, 2000; Dietsch and Petey, 2002; and Poudel, 2012). Particularly, credit risk originates from a situation, where a debtor fails to oblige the debt and it has a sizable impact on the VAR (Value-at-Risk) estimates of the banks. Typically, commercial banks face with credit risk issue, and retail loans are the largest and most obvious source of this type of risk (Al-Tamimi and AL-Mazrooei, 2007; Goyal and Joshi, 2012). Credit risk provisions are reflected by the banks' capital adequacy ratio, where almost 70% of capital is allocated for credit risk and the rest for market adjusted risk (Bhattacharya and Sinha Roy, 2008). Over the last decade, a number of international banks have developed sophisticated assessment systems in an attempt to model credit risk. The focus of such models is to aid decision makers in banks to quantify and manage risk efficiently. The output of these models play increasingly important role in banks' risk measurement and performance management process, such as customer profitability analysis, and risk-based pricing (Crouhy et al., 2000; Campbell, 2007).

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In this study, we employ a unique set of variables based on banks' internal explicit knowledge to examine credit risk based on default personal loans of Jordanian banks. Several prior studies (see Altman and Saunders, 1998) have used different methods and credit risk indicators of banks, i.e. net loans, bad debt provision, interest coverage, suspended interest, gross loan, and bad loans etc. or a combination of these measures with non-financial items. However, the credit strategy of Jordanian banks depends on the internal explicit knowledge of their borrowers. Thus, we use a set of parameters (variables) consistent with the measures, used by the Jordanian banks, such as loan amount, educational level, occupation, marital status, age, and gender of borrowers to examine the risk of default and to what extent they affect the probability of credit risk? Previous works by Zorn and Lea (1989); Quercia and Stegman (1992); Hsieh (2004); and Xu and Walton (2005) have used broadly similar measures in their studies. We explore by using internal implicit knowledge of Jordanian banks in assessing probability of default or non-performing personal loans and their subsequent implications. In addition, we investigate to what extent variables such as loan amount, bank's location and a combination of customer-bank-age affect the risk of default.

This study offers a novel perspective to credit risk literature within the Asia-Pacific and Middle-Eastern regions since risk measures used in our analysis are subjective; whereas, other studies have mainly used conventional accounting and/or financial measures of risk. In addition, it advances a quantitative specification to evaluate the chances of default by non-performing personal loans, thus captures the extent of credit risk posed by the borrowers. The findings of this study could aid to the decision support system of banks, those are heavily reliant on personal information of borrowers. Moreover, by comparing other commonly used credit risk models with our model, our study provides a clear understanding of model utility in terms of classificatory accuracy and robustness.

1. Methods of predicting credit risk

Several credit risk evaluation systems are based on some form of the judgemental-based system, which makes quantifying risk a big challenge (Fensterstock, 2005; Cheng and Neamtiu, 2009). Jordanian banks emphasize on subjective measures to assess personal loans, thus they become over reliant on their internal knowledge of customers. Typically, in a well-built financial system, risk management is on the downstream and risk prediction is on the upstream (Yeh and Lien, 2009). However, Jordanian banks lack a consistent approach to manage credit risk, thus fail to predict the credit risk and incur large default or non-performing personal loans. To build a credit scoring model, it is critical that there is a portfolio of large sample of previous customers with their application details, behavioral patterns, and subsequent credit history (Jarrow, 2001; Ong et al., 2005). Credit scoring is a set of decision models, and their underlying techniques facilitate decision making process for granting the loans. These techniques decide who will get credit, how much credit should borrowers get, and what operational strategies will improve the profitability of the banks (Altman et al., 2006).

The risk of default estimation has been improved by credit scoring models by including other aspects of credit risk management at the pre-application stage (identification of potential borrowers), at the application stage (identification of acceptable borrowers), and at the performance stage (identification of possible behavioral patterns of existing borrowers) (Bakshi et al., 2001). An earlier Basel's report (2004) stipulates two approaches of estimating the risk of default, one is conditional, and another is unconditional (see Table 1). The revised Basel report (2014) almost agrees with these approaches with different re-captions only, where unconditional approach is now referred as internal-rating based approach, and conditional approach is now referred as standardized approach.

Table 1. Approaches of credit risk management

Approach	Example	Description
Unconditional approach*	Unexpected losses (UL) approach, Credit metrics and Credit risk	These models base EDF** (expected default frequency) and derived correlation effects on relationships between historical defaults and borrower-specific information, such as internal risk ratings.
Conditional approach*	McKinsey and company's credit portfolio view	The rating transition matrices are functionally related to the situation of the economy, as the matrices are modified to give an increased likelihood of an upgrade (and decreased likelihood of a downgrade) during an upswing (downswing) in a credit cycle.

Note:* Under revised Basel report, 2014 the unconditional approach is now referred as internal-rating based approach, and conditional approach is now referred as standardized approach. ** Expected Default Frequency represents the probability of default within a given time horizon, typically one year. EDF analysis is crucial in strengthening risk measures of banks. EDFs help banks for their risk, capital and asset management. This is a core compliance measure of Basel II and III.

Practitioners distinguish between conditional models that attempt to incorporate information on the state of the economy, such as levels and trends in domestic and international employment, inflation, stock prices and interest rates, and even indicators of the financial health of particular sectors, and unconditional models reflect relatively limited borrower or facility-specific information (Chabane et al., 2004).

2. Jordanian banks and credit risk

The banking and financial intermediary system in Jordan, as a whole account for an average 17% of Jordan's GDP. At the end of 2014, there were 25 banks operating in Jordan: 13 national commercial banks, 8 foreign and 4 Islamic banks (Central Bank of Jordan, 2014). The banking system in Jordan has JOD (Jordanian Dollars) 17.8 billion in assets and a vast network of branches covering about 11,900 persons per branch on an average. However, the three largest banks account almost for 55% of the total assets, i.e. the Arab Bank dominating the sector with 29% of all assets, the Housing Bank as the second largest with the most extensive branch network, and the Jordan National Bank is the third (Central Bank of Jordan, 2014). Overall, Jordan's banking system is privately owned, well-developed, profitable and efficient, and its banks are advanced in comparison with the other banks in the region (Siam, 2007). Despite this relatively high level of development for this region, the need for more financial development is still obvious throughout the Jordanian economy (Richard, 2003). The funds in Jordanian banks are mainly used to grant loans for the private and public sectors. In addition, they deposit with national and international banks, and invest in institutional stocks and governments bonds. The rate of loans and advances to total credit facilities increased from 59.6% in 2008 to 86.1% by the end of 2014 (Central Bank of Jordan, 2014). Although Jordanian banks are relatively healthy organizations, they operate profitably, but they need to manage risk more efficiently (Siam, 2007). While the international average for default rates for retail loans is lower than 5-6% (Central Bank of Jordan, 2008, 2010), in Jordan default retail loans are estimated to be in the region of 11% compared to the Arab world's average of 5.65% during 2008-2009 (IMF, 2016). Jordanian banks are not effective lenders since their percentage of bad loans to gross loans is exceedingly high. This suggests the critical problem Jordanian banks are experiencing and their need for finding effective solutions to reduce the rate of defaults. Particularly, they require a robust and consistent framework that, in effect can manage their credit risk sufficiently.

Jordanian banks lack formalized knowledge for developing knowledge-based decision support systems to help with managing credit risk (Mashhour and Zaatreh, 2008). Siam (2007) finds banks in Jordan face uncontrollable loans due to mismanagement, flawed lending policy and illegal manipulation in lending, mainly based on their personalized knowledge of the customers. Most of the problems, in fact, are internal to the banks themselves. In 2007, the Financial Market International (FMI) found that Jordanian banks are not effective lenders. In particular, Jordanian banks lend on the basis of personal relationships and only in some cases on collateralization. Moreover, credit officers in Jordanian banks evaluate credit risk subjectively (Ministry of Planning and International Cooperation, 2007).

3. Data and methodology

3.1. Data. To create our dataset, we included all banks operating in Jordan during our sample period from 1999 to 2014. Altogether, there are 25 banks listed under the directory of Central Bank of Jordan (CBJ, 2014). At first, 8 banks are excluded from the dataset, since they have either full or majority of foreign ownership stake. In addition, 4 other banks are further eliminated due to missing and unavailability of data, as they are primarily Islamic banks or branches of Islamic banks. Hence, the final number resulted in 13 banks. Next, we identified a sample of 2755 default or non-performing loan profiles of individual borrowers from these 13 banks. The loan profiles of individual borrowers are privately collected from each bank under data protection guidelines, where each individual profile is strictly anonymized. The loan profiles of individuals are determined based on five criteria. The criteria are laid out as- 1) at least three consecutive monthly arrears[1] or five arrears over two years from the beginning of loan period, 2) at least two formal notices of late payment are served over two years, 3) no satisfactory payment plan is proposedby the borrowers to consider a repayment plan, 4) the non-payment loan amount is less than 2/3 of the collateral, if applicable, 5) after relaxing the repayment dates, the scheduled payments are not complied with. To estimate our model, we create a matched sample of 2755 performing loan profiles of individual borrowers from these 13 banks. Based on above 5 criteria, the performing borrowers have maintained timely repayment and not violated any terms and conditions, as stipulated by the contractual agreement from the beginning of the loan period. The variables selected under performing loan profile exactly match with the default or non-performing loan profile variables.

The sample of loan profiles includes several financial and non-financial variables of the banks, those are used mainly for the assessment of loan provision in Jordanian Banks. The variables are compiled by the banks through knowing the customers at personal level, often known as internal explicit knowledge. Table 2 describes the variable definitions. The dependant variable is 'Perform (PERF)', which indicates a satisfactory or unsatisfactory record of re-

[1] As subject to loan terms and conditions, i.e. only interest payment, and/or interest with principal.

payments on a loan. This variable is a binary choice unobservable predictor, i.e. 0 indicates 'default or non-performing loans' and 1 indicates 'performing loans'. Hence, PERF captures the probability of credit risk arising from default personal loans. The potential risk measures are explanatory or independent variables (based on internal explicit knowledge) and divided into two groups. The group one includes non-financial variables, i.e. occupation, educational level, marital status, age and gender. The other group includes a combination of bank specific financial and non-financial variables, i.e. loan amount, bank's location and customer-bank-age. The selection of variables included in this study is mainly based on Jordanian banks' choice of measures for credit risk assessment posed by personal lending.

Table 2. Credit risk variable description

Variable	Description
PERF	Represents a binary choice latent variable, stands for the borrowers' loan payment. Where 0 denotes default or non-performing loan and 1 indicates performing loan.
OCC	OCC denotes the occupation of the borrowers, where; 1 represents 'Unemployed or others', 2 represents 'Governmental or Public sector employees', 3 represents 'Private or General Management and administrative employees'.
CBA	CBA stands for the amount of time in years the borrowers have been with the bank. CBA denotes 1 for equal to or less than 2 years, 2 for two years to five years, and 3 for more than five years.
INC	INC is the monthly income of the borrowers in Jordanian Dinar, where; low income group stands for 1 (200-999 JD), mid income group represents 2(1000-1999 JD) and high income group represents 3 (≥ 2000 JD).
AGE	AGE denotes the age of the borrowers in years. AGE is represented by 1 for the younger group (19-30 years), 2 for middle group (31-59 years), and 3 for senior group (≥ 60 years).
EDU	EDU is the level of educational qualification achieved by the borrowers, denotes as 1 for undergraduate/degree, 2 for post-graduate/masters and above, and 3 for other qualifications.
LAM	LAM is the loan amount that the borrowers have taken, denotes as low amount for 1 (≤ 10,000 JD), mid amount for 2(10,001-99,000 JD), and high amount for 3(≥100,000 JD).
MAR	MAR denotes the marital status of the borrowers, 1 if married and 0 otherwise.
GND	GND represents the gender of the borrowers, denotes 1 for male and 0 for female.

3.2. Variable description. Each variable is assigned scale values based on their different levels. Therefore, each attribute variable is converted into dummy variables. OCC denotes the occupation of the borrowers, where; 1 represents 'Unemployed or others', 2 represents 'Governmental or Public sector employees', 3 represents 'Private or General Management and administrative employees'. CBA stands for the amount of time in years the borrowers have been with the bank. CBA denotes 1 for equal to or less than 2 years, 2 for two years to five years, and 3 for more than five years. INC is the monthly income of the borrowers in Jordanian Dinar, where; low income group stands for 1 (200-999 JD), mid income group represents 2 (1000-1999 JD) and high income group represents 3 (≥ 2000 JD). AGE denotes the age of the borrowers in years. AGE is represented by 1 for the younger group (19-30 years), 2 for middle group (31-59 years) and 3 for senior group (≥ 60 years). EDU is the level of educational qualification achieved by the borrowers, denotes as 1 for undergraduate/degree, 2 for post-graduate/masters and above, and 3 for other qualifications. LAM is the loan amount that the borrowers have taken, denotes as low amount for 1 (≤ 10,000 JD), mid amount for 2 (10,001-99,000 JD), and high amount for 3 (≥ 100,000 JD). MAR denotes the marital status of the borrowers, 1 if married and 0 otherwise. GND represents the gender of the borrowers, denotes 1 for male and 0 for female. Based on their scale value, we have created dummy variables for each level to run in the logistic model. Although, multicollinearity can be a pertinent issue with several dummy variables, but can be safely ignored, when the attribute variable is categorical and having multi-level values.

3.3. Methodology. We estimate a binary choice logistic model to capture the credit risk of Jordanian banks. The credit risk is specified as a proxy for the default loans[2]. For example, when the loans are defaulted over time (default or non-performing loan criteria are outlined in the above data section), the credit risk becomes higher. We examine the same variables used by Jordanian banks to measure the credit risk compiled by banks' internal explicit knowledge, i.e. knowing the borrowers through their personal knowledge. Our default or non-performing loan and performing loan profile variables are used in the logistic model in one run. We construct the generic logistic model as follows:

$$\begin{aligned} Y^*_{i,t}(\pi) &= \alpha_0 + \alpha_1 OCC_{i,t} + \alpha_2 CAS_{i,t} + \alpha_3 INC_{i,t} + \\ &+ \alpha_4 AGE_{i,t} + \alpha_5 EDU_{i,t} + \alpha_6 LAM_{i,t} + \alpha_7 MAR_{i,t} + \\ &+ \alpha_8 GND + \varepsilon_{i,t}, \end{aligned} \quad (1)$$

where $Y^*_{i,t}(\pi)$ is a binary choice latent variable, defined as the observable 0, 1; where 0 indicates 'default or non-performing loan' and 1 indicates 'performing loan'. $Y^*_{i,t}(\pi)$ gives the logistic transformation with the log-odds $Ln(\frac{\pi}{1-\pi})$. A positive and significant value of any variable coefficient indicates that the variable significantly contributes to the credit risk. In addition, we supplemented our analysis by comparing the logistic estimate with alternate models, commonly used for credit risk analysis. We aim to find if any other alternate model

[2] Basel Committee recommendation, 2010 and 2014.

could offer better results by improving the credit risk prediction. West (2000) and Ong et al. (2005) find that with an improvement even to a fraction of a percentage in credit accuracy leads to significant savings for the banks.

We expect that borrowers without a job are more likely to default, while for the variable income, we predict that borrowers with higher income would have lower probability of default. Hayashi (1987) observes that borrowers with low income are more likely to default. For the variable marital status (MAR), we predict that unmarried couples would be more likely to default, compared to married couples. Quercia and Stegman (1992) find that unmarried or divorced borrowers are more likely to default than married ones. We also expect educated customers would have lower probability of default. Chatterjee et al. (2007) find that uneducated and unskilled borrowers are at a high level of risk. For the variable age (AGE), we expect that younger clients would have higher probability of default. For both the variables loan amount (LAM) and customer-bank-age (CBA), we suppose lower loan amount and new borrowers are less likely to default. In particular, under customer-bank-age (CBA), new customer would have lower probability of risk, whereas customers longer with the bank are more likely to default.

4. Empirical results

4.1. Robustness test. As an initial robustness check, we ran all the explanatory variables under logistic regression and deleted the outliers, those have reported Studentized residuals larger than ± 3. Presence of outliers can potentially limit the chances of model accuracy and lead to biased coefficient estimation (Christensen, 1997). In addition, we checked all the diagnostics of our model. The Hosmer and Lemeshow test was not significant suggesting our model is reliable. Also, we found that the Omnibus statistic is significant, indicating a parsimonious model. However, to ascertain any unobservable estimation issue, we conducted further robustness check. Therefore, we used Bianco and Yohai's (1996) robust logistic regression, introduced by Croux and Haesbroeck (2003) to evaluate the classification accuracy and robustness of model. The robust logistic regression includes a bounded function and a bias correction term to produce a higher model classification. Contrasting both the models we found that the results do not differ at statistical level, as we obtained same p-values for our explanatory variables with consistent statistical significance. The only difference observed was the reduction in the value of standard errors. However, the difference was relatively marginal. This suggested that the corresponding Wald z statistics of the variables are not going to be changed much to derive a different interpretation of results. This leads to consider our model specification is robust and goodness-of-fit measure is satisfied.

4.2. Summary statistics. Table 3 presents the descriptive statistics for both the default or non-performing loan and the performing loan profiles. All the variables in the sample are recorded as scale variables; therefore, the mean and median values are not reported, while frequency distribution and percentages are reported.

Table 3. Descriptive statistics of the credit risk variables

Variable	Description	Code	Panel 1		Panel 2	
			Default or non-performing loan		Performing loan	
			Frequency	Percentage	Frequency	Percentage
OCC	Occupation	1	171	6.21%	23	0.83%
		2	1432	51.98%	1489	54.05%
		3	1152	41.81%	1243	45.12%
CBA	Customer-bank-age	1	1645	59.71%	987	35.83%
		2	765	27.77%	1121	40.69%
		3	345	12.52%	647	23.48%
INC	Income	1	675	24.50%	476	17.28%
		2	1757	63.77%	1311	47.59%
		3	323	11.72%	968	35.14%
AGE	Age	1	1084	39.35%	659	23.91%
		2	976	35.43%	1409	51.14%
		3	695	25.23%	687	24.94%
EDU	Educational level	1	967	35.10%	798	28.97%
		2	766	27.80%	932	33.83%
		3	1022	37.10%	1025	37.21%
LAM	Loan-amount	1	1222	44.36%	1432	51.98%
		2	989	35.90%	1126	40.87%
		3	544	19.75%	197	7.15%

Table 3 (cont.). Descriptive statistics of the credit risk variables

Variable	Description	Code	Panel 1		Panel 2	
			Default or non-performing loan		Performing loan	
			Frequency	Percentage	Frequency	Percentage
MAR	Marital status	1	1881	68.30%	1902	69.04%
		0	874	31.70%	853	30.96%
GND	Gender	1	2354	85.40%	2451	88.97%
		0	401	14.60%	304	11.03%

Note: A total number of 2755 default or non-performing loan profiles and 2755 matched performing loan profiles are included in the descriptive statistics. OCC denotes the occupation of the borrowers, where; 1 represents 'Unemployed or others', 2 represents 'Governmental or Public sector employees', 3 represents 'Private or General Management and administrative employees'. CBA stands for the amount of time in years the borrowers have been with the bank. CBA denotes 1 for equal to or less than 2 years, 2 for two years to five years, and 3 for more than five years. INC is the monthly income of the borrowers in Jordanian Dinar, where; low income group stands for 1 (200-999 JD), mid income group represents 2 (1000-1999 JD), and high income group represents 3 (≥ 2000 JD). AGE denotes the age of the borrowers in years. AGE is represented by 1 for the younger group (19-30 years), 2 for middle group (31-59 years) and 3 for senior group (≥ 60 years). EDU is the level of educational qualification achieved by the borrowers, denotes as 1 for undergraduate/degree, 2 for post-graduate/masters and above, and 3 for other qualifications. LAM is the loan amount that the borrowers have taken, denotes as low amount for 1 (≤ 10,000 JD), mid amount for 2 (10,001-99,000 JD), and high amount for 3 (≥ 100,000 JD). MAR denotes the marital status of the borrowers, 1 if married and 0 otherwise. GND represents the gender of the borrowers, denotes 1 for male and 0 for female.

Under occupation (OCC), the largest group is the government or public sector employees representing 51.98% and 54.05% respectively for both the loan profiles. It is interesting that the number of unemployed borrowers largely differ between both the loan profiles. There are 6.21% unemployed within default or non-performing loan profile, while a marginal 0.83% unemployed under performing loan. The amount of time a borrower has been with a bank (CBA) indicates that the majority of default borrowers are banking with their banks almost less than 2 years. However, performing loan profile suggests that 40.69% borrowers are with the bank between 2 to 5 years. The smallest group of borrowers under both the loan profiles are with the bank for more than 5 years. For the income (INC) variable, most of the borrowers earn between 1000 to 1999 JD per month, whereas; the high income group, i.e. more than 2000 JD per month represents 35.14% of the total performing loan profile and only 11.72% of the default or non-performing loan. The low income group, i.e. borrowers earning less than 999 JD per month represents 24.50% of default loan profile and 17.28% of performing loan profile.

The age (AGE) of borrower for the default loan profile shows that 39.35% of borrowers' age falls below 30 years; while for the performing loan, 23.91% of borrowers are below 30 years. The largest age group, i.e. 51.14% for performing loan is between 31 to 59 years. Under educational qualification (EDU), most of the borrowers have achieved a degree or a master's qualifications. The loan amount variable indicates that 44.36% default loan borrowers and 51.98% performing loan borrowers have taken loan below 10,000 JD. Interestingly, only 7.15% performing loan borrowers compared to 19.75% default loan borrowers have taken a high loan amount, equal to or more than 100,000 JD. Most of the default and performing borrowers are married, and male for both the marital status (MAR) and gender (GND) variables.

4.3. Bivariate correlation. The bivariate correlation results are presented in Table 4. Panel 1 reports the default or non-performing loan sample results, and Panel 2 reports performing loan sample results. Most of the variables indicate significant positive relationship with exception to a few variables. Income (INC), Age (AGE), Education (EDU) and Loan amount (LAM) are negatively significant with Customer-bank-age (CBA) group for the default or non-performing loan profile, whereas; for the performing loan profile only education (EDU) is negatively significant. For both the loan profiles, education (EDU) is negatively significant with marital status (MAR), suggesting married borrowers are more likely to have at least a degree or master's qualification. Marital status (MAR) and gender (GND) are negatively significant with loan amount (LAM) for the default or non-performing loan profile, indicates that the unmarried or female borrowers are likely to have low income, i.e. below 999 JD per month.

Table 4. Correlation results of credit risk variables

Panel 1. Default or non-performing loan profile							
	OCC	CBA	INC	AGE	EDU	LAM	MAR
OCC							
CBA	-0.607^{b}						
INC	0.317^{b}	-0.219^{b}					
AGE	0.221^{b}	-0.349^{b}	0.061^{b}				
EDU	0.162^{b}	-0.123^{b}	0.278^{b}	0.009^{c}			
LAM	0.133^{b}	-0.115^{b}	0.403^{b}	0.036	0.140^{b}		
MAR	0.049^{b}	0 .152^{b}	-0.166^{b}	0.109^{b}	-0.096^{b}	-0.100^{b}	
GND	0.067^{b}	0.209^{c}	-0.121^{b}	0.032^{b}	0.114^{b}	0.021^{b}	0.008^{b}

Table 4 (cont.). Correlation results of credit risk variables

Panel 2. Performing loan profile							
	OCC	CBA	INC	AGE	EDU	LAM	MAR
OCC							
CBA	0.340[b]						
INC	0.397[b]	0.562[c]					
AGE	0.015[b]	0.202[b]	-0.044[a]				
EDU	0.183[a]	-0.082[b]	0.260[b]	0.260[b]			
LAM	0.383[b]	0.044[b]	0.014[b]	0.094[b]	0.179[b]		
MAR	0.312[b]	0.307[c]	0.128[b]	0.387[b]	-0.102[b]	0.513[b]	
GND	0.078[C]	0.312[b]	-0.665[a]	0.046[b]	0.224[b]	0.023[b]	0.011[b]

Note: A total number of 2755 default or non-performing loan profiles and 2755 matched performing loan profiles are included in the correlation analysis. OCC denotes the occupation of the borrowers, where; 1 represents 'Unemployed or others', 2 represents 'Governmental or Public sector employees', 3 represents 'Private or General Management and administrative employees'. CBA stands for the amount of time in years the borrowers have been with the bank. CBA denotes 1 for equal to or less than 2 years, 2 for two years to five years, and 3 for more than five years. INC is the monthly income of the borrowers in Jordanian Dinar, where; low income group stands for 1 (200-999 JD), mid income group represents 2 (1000-1999 JD), and high income group represents 3 (≥ 2000 JD). AGE denotes the age of the borrowers in years. AGE is represented by 1 for the younger group (19-30 years), 2 for middle group (31-59 years) and 3 for senior group (≥ 60 years). EDU is the level of educational qualification, achieved by the borrowers, denotes as 1 for undergraduate/degree, 2 for post-graduate/masters and above, and 3 for other qualifications. LAM is the loan amount that the borrowers have taken, denotes as low amount for 1 (≤ 10,000 JD), mid amount for 2 (10,001-99,000 JD), and high amount for 3 (≥100,000 JD). MAR denotes the marital status of the borrowers, 1 if married and 0 otherwise. GND represents the gender of the borrowers, denotes 1 for male and 0 for female. [a] Indicates significance at 1% level. [b] Indicates significance at 5% level. [c] Indicates significance at 10% level.

4.4. Logistic regression results. Table 5 reports logistic regression results. The column 1 represents the coefficient estimate, column 2 reports the standard errors (Std. error), column 3 and 4 represent Wald's statistics and odds ratio (e^{β}) respectively. The model suggests that the explained variance among explanatory variables is significantly greater than unexplained variance as the Omnibus model test is statistically significant at 1% level. The choice model performs better with 99.2% classificatory efficiency, than a naive proportional model. Most of the explanatory variables measuring the risk of default over performing loans are statistically significant at 1% level.

Table 5. Logistic regression results of the credit risk variables

Variable	Coefficient	Std. error	Wald's χ^2	e^{β} (Odds ratio)
Constant	19.926[a]	3.184	39.157	0.000
OCC(1)	12.496[a]	0.956	6.820	2.134
OCC(2)	5.388	1.617	11.100	0.014
OCC(3)	-5.340[a]	2.059	6.730	2.005
CBA(1)	2.298[a]	1.086	22.331	1.045
CBA(2)	1.334[b]	2.008	12.987	0.008
CBA(3)	2.112[b]	1.876	8.991	0.277
INC(1)	19.869[a]	3.616	30.199	2.255
INC(2)	-7.742[a]	1.739	19.827	0.002
INC(3)	-4.487[a]	1.067	17.681	8.812
AGE(1)	6.360[a]	1.166	29.762	2.002
AGE(2)	11.573[a]	1.820	40.448	1.062
AGE(3)	-2.551[a]	2.076	11.996	1.011
EDU(1)	-2.551[a]	2.076	11.996	1.011
EDU(2)	-1.897[a]	1.339	12.687	2.113
EDU(3)	2.551	2.076	11.996	1.011
LAM(1)	0.220[a]	0.074	8.838	4.803
LAM(2)	-1.177[a]	0.339	12.095	2.308
LAM(3)	-1.186[a]	0.216	30.122	0.305
MAR(1)	-0.687[a]	0.088	60.618	2.503
MAR(0)	0.968	0.972	34.567	0.088
GND(1)	1.987[a]	2.106	18.987	0.045
GND(0)	2.346	2.456	22.345	0.061
Diagnostic tests		χ^2		
Omnibus model test		176.89[a]		
Percentage correctly classified		99.2[a]		
Cox and Snell R^2		0.760		

Note: The table report logistic regression results of credit risk variables. The sample includes 2755 default or non-performing loans and a matched sample of 2755 performing loans. OCC denotes the occupation of the borrowers, where; 1 represents 'Unemployed or others', 2 represents 'Governmental or Public sector employees', 3 represents 'Private or General Management and administrative employees'. CBA stands for the amount of time in years the borrowers have been with the bank. CBA denotes 1 for equal to or less than 2 years, 2 for two years to five years, and 3 for more than five years. INC is the monthly income of the borrowers in Jordanian Dinar, where; low income group stands for 1 (200-999 JD), mid income group represents 2 (1000-1999 JD), and high income group represents 3 (≥ 2000 JD). AGE denotes the age of the borrowers in years. AGE is represented by 1 for the younger group (19-30 years), 2 for middle group (31-59 years) and 3 for senior group (≥ 60 years). EDU is the level of educational qualification, achieved by the borrowers, denotes as 1 for undergraduate/degree, 2 for post-graduate/masters and above, and 3 for other qualifications. LAM is the loan amount that the borrowers have taken, denotes as low amount for 1 (≤ 10,000 JD), mid amount for 2 (10,001-99,000 JD), and high amount for 3 (≥100,000 JD). MAR denotes the marital status of the borrowers, 1 if married and 0 otherwise. GND represents the gender of the borrowers, denotes 1 for male and 0 for female. [a] Indicates significance at 1% level. [b] Indicates significance at 5% level. [c] Indicates significance at 10% level.

We find most of the occupation groups are statistically significant except OCC (2), i.e. government and public sector employees. OCC (1) representing unemployed borrowers is positively significant at 1% level with an estimated coefficient value of 12.496 and odds ratio (e^{β}) of 2.134. OCC (3) represents private or general management and administrative employees, which is also significant with a negative coefficient value of -5.340 and odds ratio of 2.005. The results from occupation suggest that the probability of default or non-performing loan increases almost twice, if a borrower is unemployed. Similarly, it also indicates that if a borrower is employed in a private or general management and administrative sector, then the chances of default decrease almost twice. As such unemployed borrowers are expected to default, whereas, it is interesting that people in public sector are more likely to mitigate the credit risk, given that government and public sector employees do not influence the chances of default. The growing trend of private sectors in Jordan, as well as the relatively low salary of public sector could be the reasons that private sector employees are less likely to default, rather they support decreasing the chances of credit risk. CBA i.e. the number of years the borrowers banking with their banks measures significant impact of credit risk (Saurina and Jimenez, 2006). All three levels of CBA are positively significant. However, only CBA (1) denotes a reported odds ratio (e^{β}) above 1. The borrowers relatively new to a bank, banking less than or equal to 2 years are most likely defaulter for non-performing loans. Since most of the Jordanian banks pursue wider initiative for larger customer base following Central Bank of Jordan's (CBJ) directives (2006), it is plausible that banks are recruiting sizable number of new customers and allowing them relaxed loan provisions.

All income (INC) groups are statistically significant, however the mid income group INC (2) and high income group INC (3) have negative coefficient values. The mid income group, i.e. borrowers earn 1000 to 1999 JD per month, does not demonstrate any sizable impact on probability of default, as it reports a marginal odds ratio of 0.002. The low income group INC (1), which represents borrowers earning less than 999 JD per month, reports an odds ratio of 2.255, suggesting that borrowers in this group are more than twice likely to default. The high income group, which denotes borrowers earning more than 2000 JD per month, are most likely to decrease the chances of default almost by 8 times. We find this is consistent with our expectation, although the credit risk reduction by a margin of 8 times appears excessive. Younger and mid age borrowers represented by AGE (1) and AGE (2), are positively significant, where the senior group is negatively significant. Younger borrowers those are below 30 years of age are highly likely to default and their chances of default increase almost twice. This is consistent with the findings of Chatterjee et al. (2007).

The senior borrowers, on the other hand significantly lower the probability of default.

EDU (1) i.e. borrowers having a degree qualification and EDU, (2) i.e. borrowers having a postgraduate or master's qualification are negatively significant excluding EDU, (3) i.e. borrowers having other qualifications, which is statistically insignificant. EDU (2) reports odds ratio (e^{β}) of 2.113. Thus, the borrowers that have achieved a postgraduate or master's qualification are most likely to lower the probability of default by almost twice. Loan amount (LAM) represented by low, mid and high loan amount are statistically significant, however high loan amount LAM (3) i.e. an amount equal to or more than 100,000 JD indicates a marginal odds ratio. Borrowers having a low loan amount LAM (1) i.e. less than or equal to 10,000 JD, are most unlikely to default, rather lowers the chances of default almost by 4 times. However, the mid loan amount LAM (2) i.e. a loan amount between 10,001 JD to 99,000 JD increases the probability of default by almost twice. Since we find high income and mid income group borrowers lower the chances of default, it is possible that mid loan amounts are manageable by those groups. Whereas, low income group could typically struggle with the loan. We find marital status MAR (1) i.e. married borrowers is negatively significant with a reported odds ratio of 2.503. This suggests married borrowers are likely to lower the chances of default by almost two and half times. Similarly, gender GND (1) i.e. male borrowers is statistically significant, but denotes a marginal odds ratio of 0.088.

5. Supplementary analysis

To evaluate the best performing model, we examined by comparing 6 other commonly used credit risk models. Different algorithm based models are regularly used to predict the risk of default i.e. CHAID, QUEST, Decision Tree, C 5.0, Bayesian Net, and Neural Network (NN). These models are known as decision support models. The models help decision makers of banks in granting loans by evaluating the chances of credit risk. We present a comparative estimate of all the models in Table 6.

Table 6. Comparison between the commonly used credit risk models

Model	Type I error	Type II error	F-score	PCC	PIC	Accuracy
Logistic regression	9.7	0.8	94.3	99.2	89.3	97.9
CHAID	17.2	4.1	87.4	95.7	79.1	93.9
QUEST	6.8	5.3	88.6	94.4	82.7	94.5
Decision tree	11.8	4.3	91.0	95.5	86.5	94.6
C 5.0	16.0	5.8	87.4	93.8	81.0	92.7
Bayesian net	10.8	7.7	89.8	91.6	87.9	91.8
Neural networks	11.0	1.9	92.8	98.1	87.5	96.8

Note: The sample includes 2755 default or non-performing loans and a matched sample of 2755 performing loans. Each model has been tested by employing same variables used for the logistic regression. Type I and Type II error denote *false positive* and *false negative* rejection of hypothesis respectively. F-score denotes test model robustness. 1 stands for best value measure. PCC stands for Percentage Correctly Classified, represents classificatory accuracy of the model. PIC stands for Percentage Incorrectly classified, represents classificatory inaccuracy of the model. Accuracy represents, how well the choice model performs better than a naive proportional model.

Curram and Minguers (1994) have used decision tree based models. Decision trees are powerful and popular tools for classification and prediction. The fact that decision trees can readily be summarized graphically makes them particularly easy to interpret. Decision tree is a rule based classifier predictive model, where input transactions are mapped to draw conclusion about that set target value. One of the most important advantages of decision trees is that the inputs can be extracted and represented in the form of classification (if-then) rules (Zurada and Lonial, 2005). Particularly, it allows the probabilities of classification (perform/ non-perform) to decide the credit approval. However, decision tree can be less cognitive and more computational.

Another model that has recently been popular is based on Neural Network (NN) platform. Hui-Chung (2007) prefers Neural Network based models for their predictive accuracy. Contrary to other statistical methods, Neural Network models do not depend on the assumptions, regarding the independence and distribution of residuals or collinearity of input variables. However, the major drawback of Neural Network model is their lack of explanatory capability. While they can achieve a high prediction accuracy rate, the reasoning behind why and how the decision was reached is not available. For example, in a case of not accepting a loan or extending an existing one, it is almost impossible to determine, which input variables are exactly the key ones to prompt the rejection of loan. Therefore, it is equally difficult to explain the decision results to managers based on Neural Network models (Baesens et al., 2003; Lee and Chen, 2002; West, 2000). Logistic regression has widely been used in analyzing the risk of default loans due to its interpretative robustness and classificatory accuracy. In addition, logistic regression does not require multivariate normality, therefore it has less statistical restrictions (Serrano-Cinca and Gutiérrez-Nieto, 2013). Desai (1996) compared Neural Network, logistic regression and Discriminant analysis for examining the credit risk. He concluded that logistic regression outperforms discriminant analysis in classifying borrowers into non-performing or performing groups, however Neural Network is almost equally good as logistic regression.

We have compared all the models using our sample data. The models are evaluated for their effectiveness on several measures – Percentage Correctly Classified (PCC), Percentage Incorrectly classified (PIC), F-Score, Type I and Type II error, F-score and model accuracy against a proportional naive model (Satchidananda and Simha, 2006). Logistic regression outperformed all other models in almost all measures. Our result is largely consistent with Desai et al. (1996); Barney et al. (1999); and Zurada and Lonial (2005). More importantly, we observed that the superior performance of the logistic regression model is due to the fact that optimization of linear hyper surface values is either high or low (binary classification) has been used in our sample. Whereas, other algorithm based models have used axis oblique hyper surface (where values can be continuous) specification, thus logistic regression provides a more robust classificatory accuracy contrary to other models, when subjective measures such as internal explicit knowledge indicators are studied. In addition, we observed that each model based on their predictive classification can be used to assign a weighted score and banks could consider using an average weighted score to decide a borrower.

Discussion and conclusion

Employing a set of unique measures, known as internal explicit knowledge, we examined the credit risk posed by default or non-performing personal loans in Jordanian banks over a period of 1999 to 2014. Jordanian banks commonly use borrowers' personal and financial information referred as internal explicit knowledge to assess their credit risk. Consistent with the practice of Jordanian banks, we examined a portfolio of 2755 default or non-performing individual loan profiles against a matching sample of performing loans. In 2005, the Central Bank of Jordan (CBJ) asked the banks to adopt an internal credit rating policy to limit the credit risk since defaulting became a recurrent issue among them.

Our findings show several new evidences and capture the emerging trends of creditworthiness of personal borrowers and credit risk assessment of Jordanian banks. A judgemental or subjective assessment makes quantifying risk a big challenge and combines many disadvantages (Fensterstock, 2005). However, our study provides a process to identify risky defaulters, which makes risk evaluation explicit, systematic and consistent. The most significant offering from our study suggests that the credit risk assessment in Jordanian banks need not to rely on internal explicit knowledge, rather the proposed model is more robust and appropriate for evaluating risk of default. This model is capable of improving personal lending process in Jordanian banks, making it more quantitative, objective and dependable instead of using a judgemental-based system as practiced. Moreover, this model based on logistic iteration is adequately superior compared to other credit risk decision models. Characteristically, the model is an ideal tool for pre-assessing the potential chances of default and specifying creditworthiness of personal borrowers. Particularly, classifying the different groups of borrowers, based on their profile and running the model with quantifiable results, makes the proposed model very effective for Jordanian banking system.

Our results suggest unemployed borrowers cause significant default or contribute significantly to non-performing loans; whereas, borrowers employed in private sectors help lowering the credit risk almost twice. We do not find any explicit evidence that borrowers from government or public sector have any significant impact on credit risk. We suppose that the private sector employees are less likely to default because of their relatively higher salary. In addition, it lends credence to the fact that Jordanian private sector employees are seen as safer, since they have better insurance provision in place to offset any eventuality that may arise from financial short-fall or unforeseen ill health. Recently, Jordan has introduced a number of measures to provide health insurance and offer better social security for wider socio-economic classes (Ministry of Planning and International Co-operation, 2014). Clearly, this trend indicates an emerging market-economy in Jordan that reflects the force of impact on social renewal of Jordanian financial system and beyond.

We also find that the new borrowers, banking with their bank less than 2 years, are most likely defaulter for non-performing loans. Since most of the Jordanian banks are engaged in recruiting a sizable number of new customers and allowing them relaxed loan provisions, the number of new borrowers have increased, so as the proportion of non-performing loans. This indicates that banking system and financial intermediaries in Jordan are now open to liberalization and embracing more customer-centric approach. In spite of these measures being counterproductive, it appears that banks are pursuing such measures in anticipation to receive long-term benefits under a reforming economy, as liberalization is a relatively new measure in Jordan.

The low income borrowers, earning less than 999 JD per month, show a noticeable chances of default, whereas; the high income borrowers, i.e. earning more than 2000 JD per month, are most likely to lower the non-performing loans by a substantial margin. We also find younger borrowers, age below 30 years very much increase the probability of default and senior borrower, over 60 years are less likely to default rather significantly lower the probability of default. Educated borrowers, those have achieved at least a degree or master's qualification lower the chances of non-performing loans. In other words, here, education implies financial literacy, thus borrowers with higher level of education clearly understand the negative implication of default loan and attempt to lower it by adhering to lending regulation. Our findings, in a way suggest that education can potentially create sustainable financial system.

Borrowers taken a loan amount between 10,001 JD to 99,000 are very likely to increase the probability of default by almost twice. On the contrary, borrowers with smaller loan amounts i.e. less than 10,000 JD potentially lower the chances of default by reducing non-performing loans. Married borrowers are most unlikely to be defaulters.

Overall, we find that the credit risk caused by default or non-performing personal loans carries a significant impact on Jordanian banking system. Although knowledge about borrowers was implicitly present in Jordanian banks, but banks were not able to make use of it in a structured and quantifiable way for managing credit risk. Our study finds and proposes a robust, quantitative and dependable model that can improve the decision making process involved with retail lending; thereby, reducing the chances of default or non-performing personal loans, which inturn, can mitigate credit-risk of Jordanian banks.

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