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Does Leverage Predict Delinquency in Consumer Lending? Evidence from Peru

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Abstract:

This paper examines to what extent household leverage—as measured by the debt-to-income (DTI) ratio—predicts delinquency in Peru's consumer credit market. A model is estimated to assess the relation between delinquency and the DTI ratio. The initial and current DTI ratios are assessed as delinquency predictors. The results confirm that the current DTI ratio is effective for predicting delinquency. This evidence supports its use in financial regulation to improve household credit risk assessment and control.

Keywords: Household finance, credit risk, consumer delinquency
JEL Codes: G20, G21, D12

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1. Introduction

Delinquency in the household credit market was at the heart of the 2007-2009 global financial crisis (Brunnermeier, 2009; Zabai, 2017). Furthermore, in recent years, many governments have been concerned about the surge in household leverage in their countries (Zabai, 2017), as there is evidence that rapid household credit expansion is highly associated with banking crises (Büyükkarabacak & Valev, 2010; Bianchi, 2011). In Peru, the financial authorities seek to improve monitoring of debt levels to prevent excessive credit risk.

Financial regulators can require banks to undertake stringent assessments of consumer lending, especially by tracking borrowers' leverage and the affordability of the loans they extend to consumers. In this context, a key indicator is the debt-to-income (DTI) ratio. Even though DTI is an objective measure of household indebtedness, it is not currently used in LAC countries' financial regulation (including Peru). At the same time, it is necessary to assess its effectiveness in measuring credit risk.

This paper discusses to what extent household leverage—as measured by the DTI ratio—predicts delinquency in Peru's consumer credit market. The dataset for 2012-2017 was obtained by merging information on outstanding debt at the consumer level from Peru's credit registry with information on income (and correlated socio-demographic indicators) from Peru's National Household Survey (ENAHO).

The results show that the initial DTI ratio is not a good predictor of future delinquency. However, changes in leverage over time—in particular increases in the DTI ratio—are strongly correlated with subsequent delinquency. A surge in DTI from 1 to 5 increases the probability of delinquency by 10 percentage points.

This paper seeks to make a contribution to the literature by evaluating the explanatory power of one of the most frequently used indicators of over-indebtedness, the DTI ratio (Lim et al, 2011; Betti et al, 2007), for predicting delinquency. This variable is not easily available due to confidentiality of information. This research provides further evidence on the determinants of personal debt delinquency (Uriarte 2016; Salinas et al. 2017; Bohórquez et al. 2017).

Researchers have used many different approaches to study this subject with differing results. D'Alessio & Iezzi (2013), using Italian household data, find that different specifications of the debt service-to-income and the DTI ratios can be used to determine whether an individual is over-indebted. Furthermore, the authors find that over-indebtedness indicators are closely correlated with economic poverty. Keese (2009) defines over-indebtedness as the debt service level that makes household income fall below a given level (e.g., the poverty line). He stresses that children are likely to cause severe household indebtedness, as they represent no-inflows and fixed expenses (e.g., food, healthcare, and education).

Other studies with similar results are Kempson (2002) and Uriarte (2016). Although they do not perform the analysis directly with the DTI or the debt service-to-income ratios (like the authors mentioned above), they find that financial problems are associated with setting up a home, supporting a family, earning low income, and aging.

Albacete et al. (2014) and Bańbuła et al. (2015) used debt service-to-income ratios in bivariate regressions where the dependent variable was debt default. This was done to determine the explanatory power of the debt service-to-income ratio. Later, once its explanatory power was tested, as in D'Alessio & Iezzi (2013), they calibrated the threshold that yields the greater power (ROC area) for predicting default.

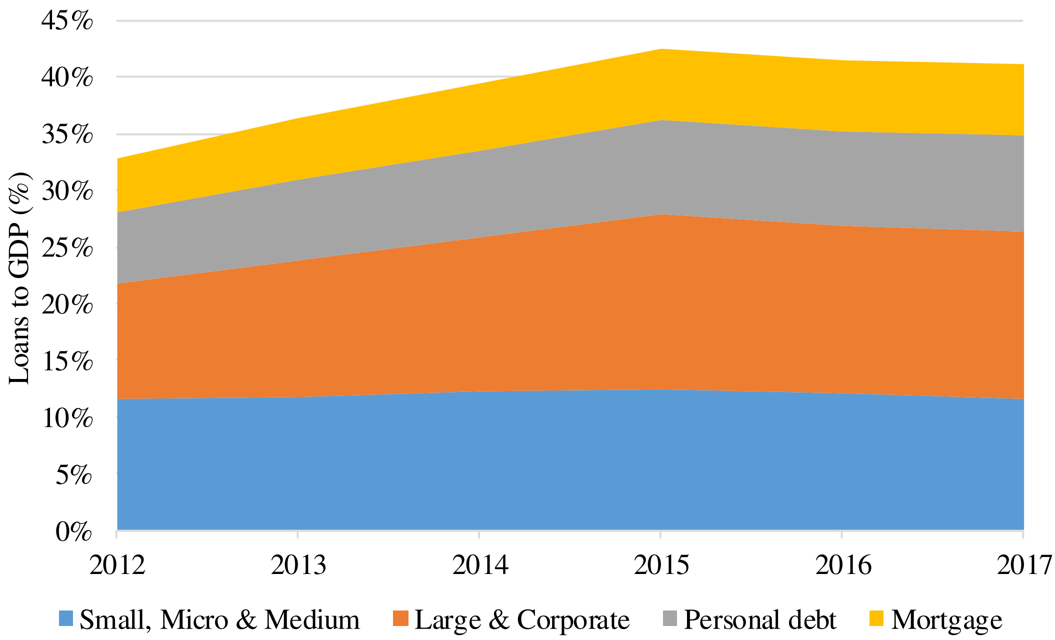
In contrast with the works mentioned above, this paper will not assume that DTI is a definition of over-indebtedness *per se*. Instead, it discusses whether it is relevant for explaining debt defaults. More specifically, it seeks to establish the explanatory power of the variable using a multivariate regression to account for the impact from other variables.

2. Background

In Peru, the total debt of the financial system was S/ 285 billion as of December 2017; i.e., 41% of GDP. The debt market can be separated in three broad categories: i) small, micro, and medium firms; ii) large and corporate firms; iii) personal debt; and iv) mortgage loans.

Total personal debt accounts for 21% of total loans. This percentage remained stable in 2012-2017. This type of debt is divided into revolving (credit cards) and non-revolving loans. Revolving loans account for 37% of total personal debt.

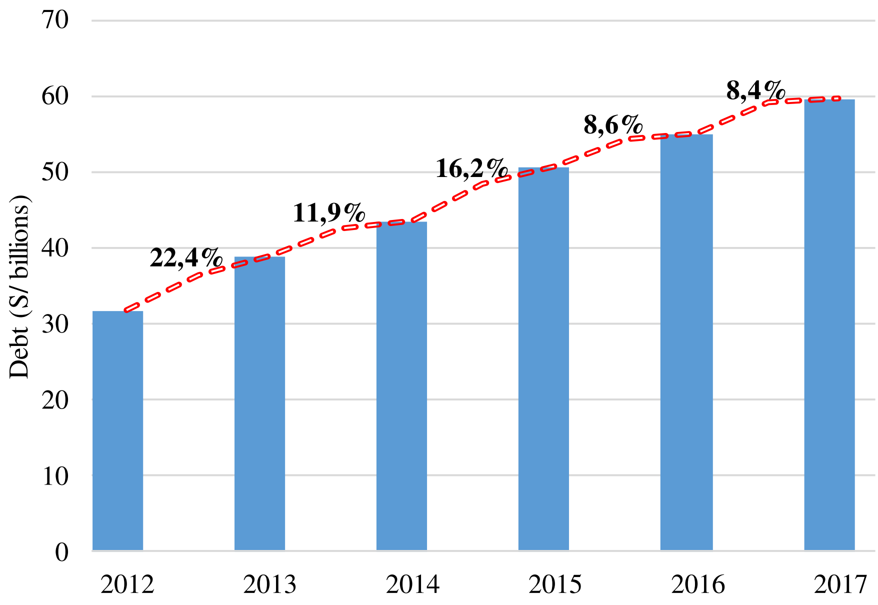
Figure 1: Composition of Peruvian financial system loans (% GDP)



In 2012-2017, personal debt grew at a declining rate (Figure 2). Although its expansion was affected by decelerating growth in those years, the value of total debt in this market almost doubled.

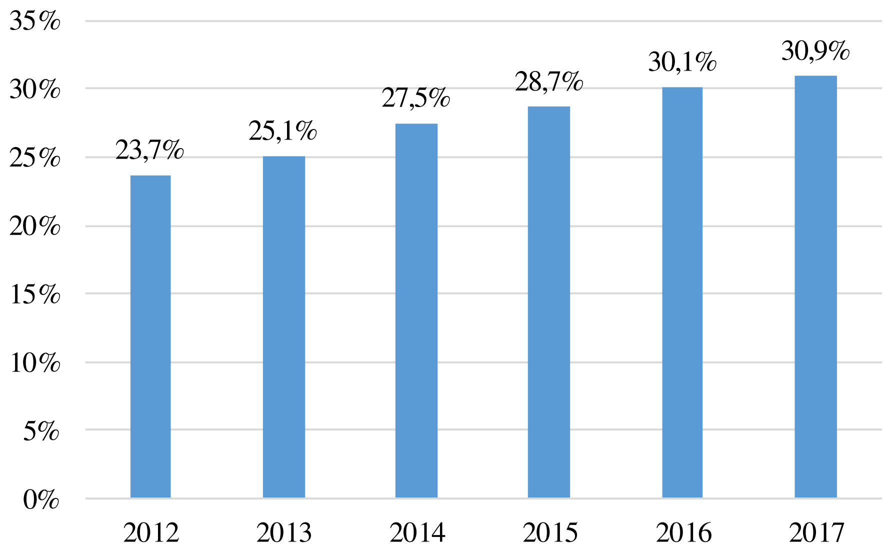
Within the personal debt market, non-revolving loans usually have a maturity of two years. However, debtors can make early repayments without paying commission charges.

Figure 2: Personal debt and annual growth



The yearly number of delinquent debtors has increased in line with growth deceleration. In 2017, around one in every three debtors had fallen into delinquency. This calculation includes the write-offs made by each financial institution. In this period, many institutions introduced changes in their credit policies and internal risk models to deal with the increase in market credit risk.

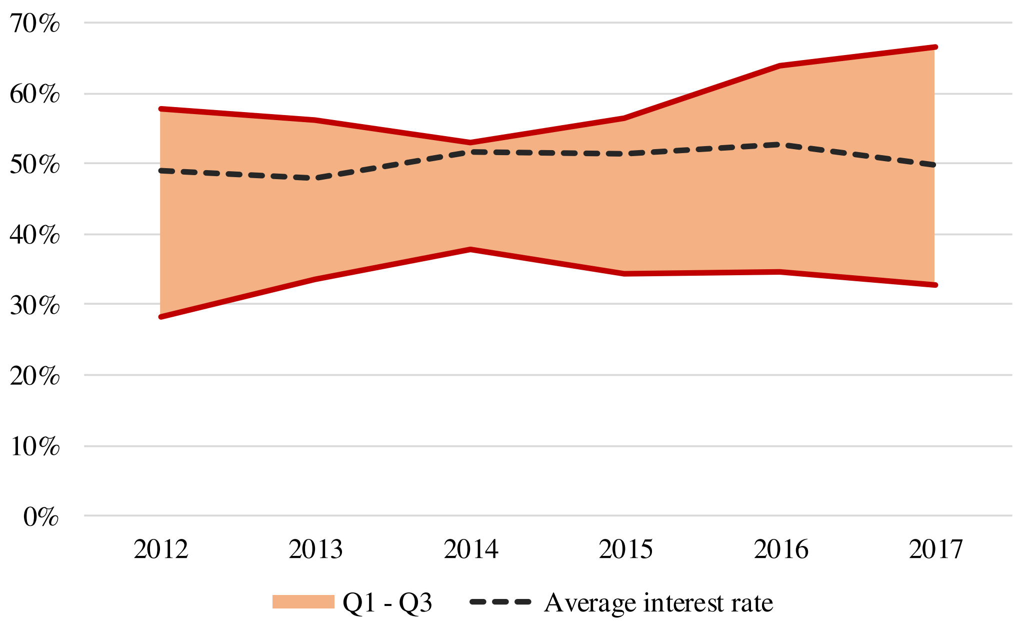
Figure 3: Debtors in delinquency



As consequence of high credit risk in the personal debt market, interest rates are high. In 2012-2017, the average interest rate on personal loans has remained at 50% on average. Over the same period, inflation remained very stable (around 3%). Thus, the real interest rate has also remained stable at high levels.

The dispersion of interest rates across financial institutions is also very high. For instance, in 2017, percentile 75 was 68%, while percentile 25 was 33%. This is because financial institutions have different target markets depending on demographic characteristics (income, geographic location, etc.), thus creating a broad spectrum of debtors with different credit risk levels.

Figure 4: Personal debt interest rates and interquartile range



Financial institutions operating in the personal debt market can be divided into three groups: the first one is made up of the four biggest banks in Peru,[1] which are also involved in several other businesses (i.e., corporate and small business loans). These banks hold approximately 60% of total personal debt. This group focuses on the medium-high income population in the formal sector. The second group is formed by four banks specialized in personal debt. These banks are subsidiaries of larger holdings that own various retail business (supermarkets, home centers, etc.); and are usually involved in the credit card business. This group represents 12% of total consumer debt. Customers in this group are usually greater risk takers than borrowers in the first group. The third group is made up of microfinance institutions. Their operations are subject to limits; e.g., some of them only grant loans and take certain kinds of deposits. They target the low-income population, often living outside the capital city. This group represents 20% of the market for consumer debt.

Although these institutions focus on different groups depending on their risk appetite, they sometimes compete with each other on certain customers with good credit profiles or live in specific regions of the country. The volume of debt that they offer is freely determined according to their credit risk models. This competition could potentially generate over-indebtedness problems.

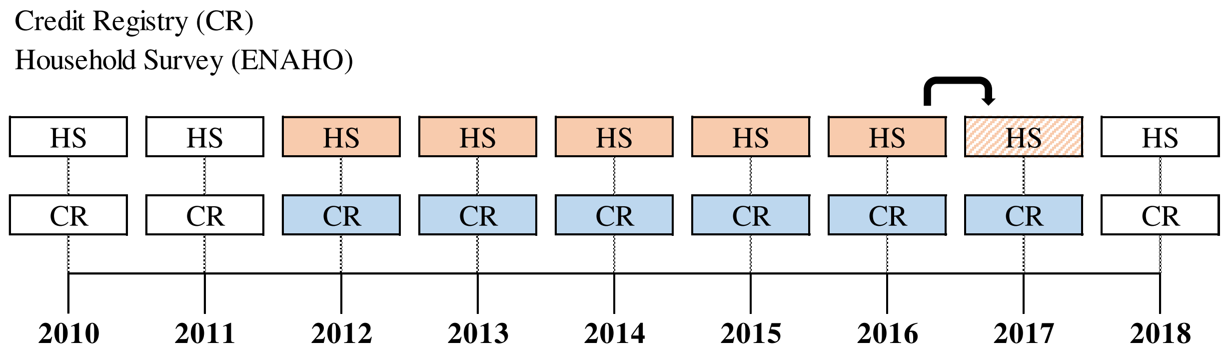
3. Data

The sample covers the period 2012-2017. The dataset is generated by the combination of two sources of information: Peru's credit registry and ENAHO.

The credit registry consists of the outstanding debt of every debtor in Peru's financial system (individuals and companies). Contract information is not available, but the original amount of loans can be established by identifying the moment when the debt was originated; i.e., when the contract amount was equal to the outstanding debt. In addition to outstanding debt, this information includes the status (no delinquency / delinquency) and the purpose of the debt (general consumption / credit card / vehicle / mortgage). The frequency of this information is monthly. In an ordinary month, there are approximately 16 million debtors in the credit registry, of which 11 million have personal debts (Table 1).

ENAHO contains variables related to socioeconomic condition (e.g., individual and household income, geographic location, age, and gender, etc.). The information is yearly and some observations are available as panel data (same people are surveyed more than one year). Peru's National Institute of Statistics conducts this survey yearly since 1997. This paper uses information from 2012 to 2016. In an ordinary year, there are approximately 93 thousand people in the survey (Table 1).

[1] As of December 2017, the market shares of these banks were as follows: Banco de Crédito 19%, Interbank 17%, Scotiabank 13%, and BBVA 9%.



Although the information from the 2017 survey was not available to complement the credit registry information, the same values of the 2016 survey are used to augment the sample.

Additionally, we have excluded mortgage loan debtors. Table 1 shows a summary of statistics about the credit registry and ENAHO. It also shows how these variables change after merging the data and performing the two following analyses.

Table 1: Sample characteristics

	People	**Average debt**	**Income**		**Delinquency**
			Individual	**Household**	
Full CR	15 973 K	20 040			31.7%
Consumer CR	11 448 K	6 137			30.9%
Full Survey	93 K		1 130	1 554	
Survey & Consumer CR	11 K	4 163	962	2 512	48.7%
Analysis 1	4 K	2 845	1 066	2 029	51.4%
Analysis 2	9 K	4 060	987	2 614	47.7%

After merging ENAHO and credit registry data, it is possible to calculate the DTI ratios. The merged data results in 10.7 thousand debtors with an average debt (S/ 4 163) lower that of the entire population (S/ 6 137).

Two separate analyses are performed using the dataset. The first one explores the effectiveness of initial DTI in predicting default at different periods (6, 12, 18, and 24 months). More specifically, we seek to establish how good DTI is at predicting delinquency in the first 6, 12, 18, and 24 months

For this reason, debtors that maintained debt before 2012 are excluded: only the debtors who did not ask for further loans after the initial one are kept in the sample. Using the entire sample would create the problem of having DTI ratios that could be far above the initial value, thus making the initial debt to income uninformative of leverage.

The second analysis is motivated by the fact that many debtors increase their debt after the initial borrowing, thereby magnifying the risk of delinquency. Debtors that registered debt before 2012 are also excluded to make this analysis comparable to the first one. This analysis explores the explanatory power of a debtor's DTI just before the event of delinquency. This analysis will determine if DTI can be used as surveillance variable to measure the evolution of credit risk.

Merging ENAHO and credit registry data provides only one thousand panel data (i.e., found in more than one year). For that reason, in the second analysis, where we need the DTI ratio to change, some assumptions are made about personal income. For example, if a debtor maintained the same outstanding debt in 2013, 2014, and 2015, and only the income information for 2013 is available, the same income is used to calculate the DTI ratio for 2014 and 2015. If other debtors' income is available for every year of debt, no assumptions are made and the DTI ratio is calculated with the available information.

The percentage of debtors that fall into delinquency according to both analyses is around 50%, which is high because the design of the analysis considers only debtors who are new to the financial system. Therefore, banks' screening for these individuals is tougher (due to lack of information) and makes it more difficult to exclude people with high credit risk levels.

The main weakness of this dataset is that ENAHO is not designed to be representative of the average debtor in the financial system.

3.1. Dependent variable

The dependent variable in the analysis is delinquency. A debtor that falls into delinquency is defined as one who has missed a payment for at least 30 days.

Since it is quite common for people simply to forget to pay their debts, arrears below S/ 50 are not considered as delinquency, because it is more likely to forget to pay such a small amount of money. In fact, the sample contains several examples of debtors in delinquency with amounts below this level that never fall in default and usually pay their debts.

As a robustness check, the relationships are tested using as dependent variable a 120-day delinquency period. When debtors are in arrears for this long, Peru's financial regulation establishes that they are in default and the financial institution must build provisions for the full amount of the debt in arrears.

3.2. Explanatory variable

In both analyses, the explanatory variable is an indicator of leverage; i.e., the DTI ratio. However, it is possible to construct two versions: using individual income and household income. From inspection of the data, the debt-to-household income is chosen. This is justified by the fact that usually household assets are available to help a member of the family, for instance, in the repayment of a debt. Furthermore, if the purpose of the loan is buying a car, a TV set, or other goods that will be available for the rest of the family, the debt burden is usually borne by all household members.

Appendix 2 shows the distribution of both DTI versions.

4. Does DTI at origination predict subsequent delinquency?

This analysis assesses how good DTI at origination is at predicting subsequent delinquency. The initial DTI is calculated and the effect on the likelihood of delinquency is estimated using a multivariate analysis.

We start separating the debtors in four groups according to the level of their initial DTI. The groups are as follows: (0-1), (1-3), (3-5) and (5+) (Figure 5). We truncated the dataset and excluded the debtors with DTI>10, since they could affect the estimation as outliers. The excluded data represent only a small part of the sample (5%).

Figure 5: Debt to Income histogram

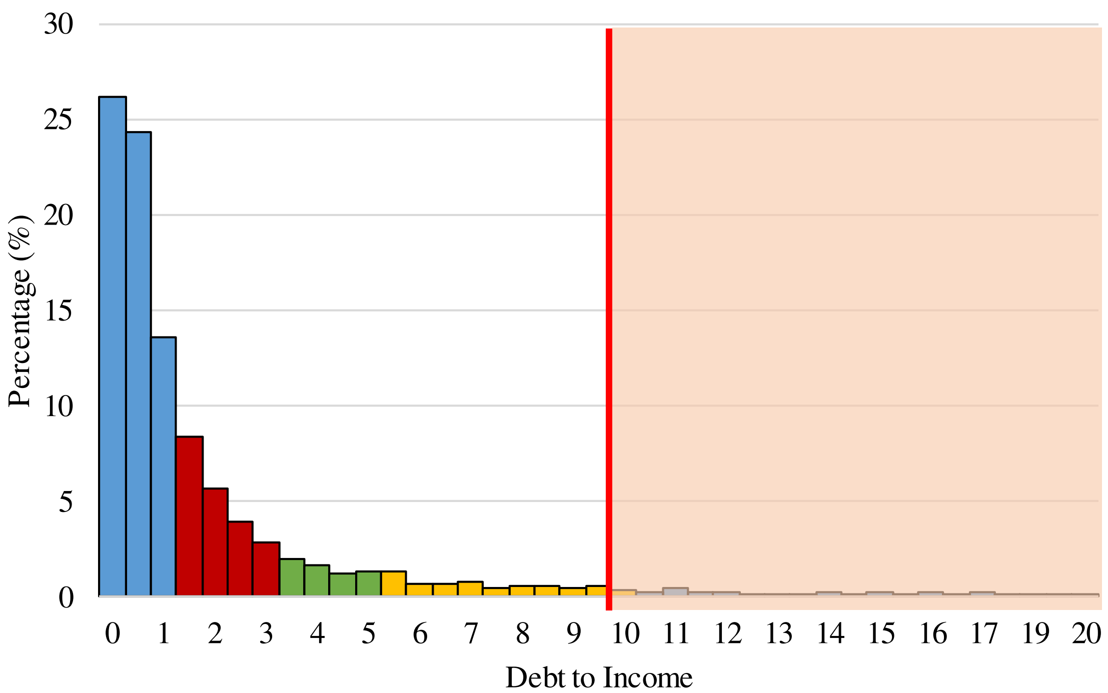
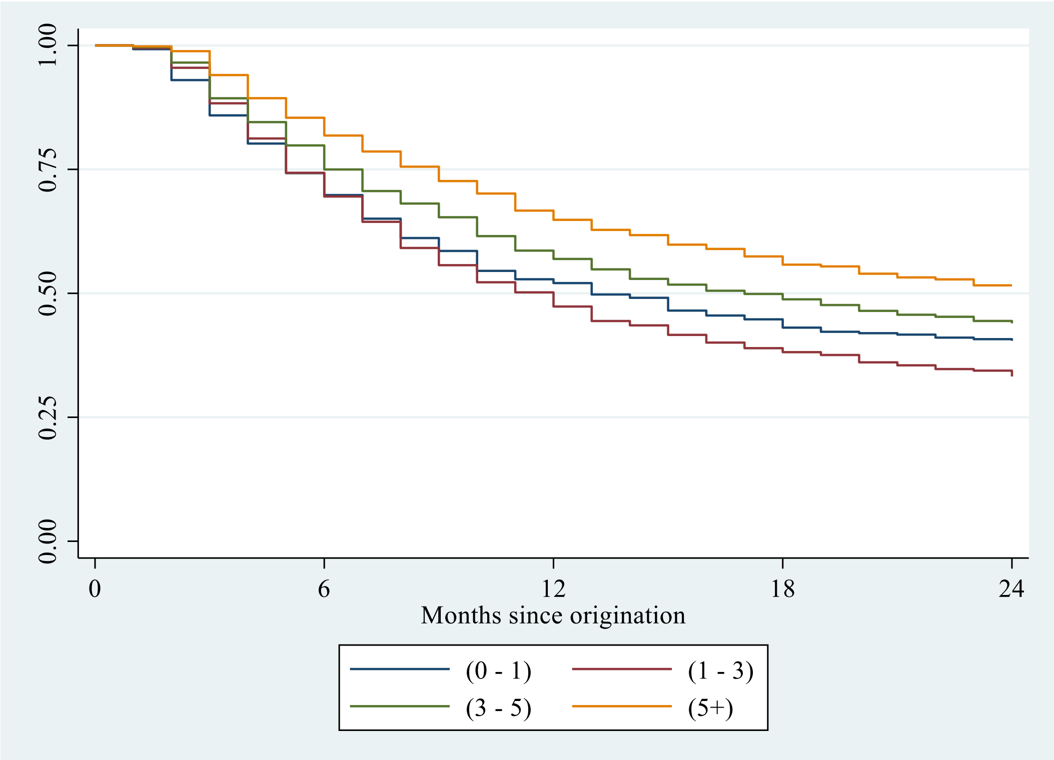


Figure 6 presents a survival graph conditional on the initial DTI. The result seems counterintuitive: borrowers who are more indebted are less likely to default. However, this could be because there are other variables influencing default. A multivariate regression is then run to control for these effects.

Figure 6: Survival graph by debt to income - Analysis 1



4.1. Methodology

Since the most common loan maturity is up to two years, we only use debtors who have maintained an outstanding debt for at last two years. This is done to avoid biases that could arise from debtors that repay their debts early; i.e., leaving the dataset before the schedule of payments is completed.

To evaluate the impact of the initial DTI ratio on the probability of delinquency, four logit models are estimated to explain delinquency. Model (1) considers all the debtors 6 months after loan origination to create a variable that takes a value of 1 if there has been a delinquency event until then, and zero otherwise. This process is repeated for 12, 18, and 24 months.[2]

The logit regression is as follow:

$$\Pr(delinquency)_i = \alpha_l + \alpha_t + \beta DTI_i + \gamma X_i + \varepsilon_i$$

α_l: Fixed effect of geographic location
α_t: Fixed effect of year of origination
X_i: Gender, Income, Age, Number of bank relationships, Number of children, Collateral

[2] A survival regression was also run (Appendix 3) and yielded the same results as the logit regression.

Fixed effects are included for geographic location and year of origination to account for heterogeneity.

Table 2 provides summary statistics for all variables employed in the analysis. As controls, the number of banking relationships is included to account for competition between financial institutions, which results in debtors having more than one debt in different institutions. However, it can be verified that most debtors only have debt with one institution; for that reason, this variable is excluded from the analysis.

The number of children is taken as a measure of family burden. This is relevant to the analysis because a larger family represents higher fixed expenses in health, food, and education, which affect the income available to repay debts.

Table 2: Descriptive statistics of the variables - Analysis 1

Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Default dummy	3 664	0,51	0,50	0	1
Initial debt (in S/000)	3 664	2,84	4,35	0,1	53
Debt to Income (Hosehold)	3 664	1,66	1,88	1,6E-02	10
Household income (in S/000)	3 664	2,29	2,03	0,1	41
Gender (Female=1)	3 664	0,30	0,46	0	1
Age	3 664	36,68	13,55	18	85
Banking relationship	3 664	1,01	0,08	1	2
Children	3 664	1,32	1,33	0	10
Collateral	3 664	0,50	0,50	0	1

4.2. Results

Table 3 shows the multivariate regression results, which still suggest counterintuitively that the higher a debtor’s leverage, the higher the probability of delinquency. After controlling for the covariates, this seems to be a strong result for all time ranges. The regression does not show collinearity problems between income and DTI; and the results are robust to the exclusion of the income variable.

This result is also consistent with the survival regression and with the alternative dependent variable (120-day delinquency). See Appendices 3, 4, and 5.

All other control variables are statistically significant and have a consistent sign, except for the number of banking relationships (which could be due to the low variance).

Table 3: Logit regression on delinquency for various time windows

This table shows the estimates of a logit model where the dependent variable is *delinquency* within different range of months after the loan origination.

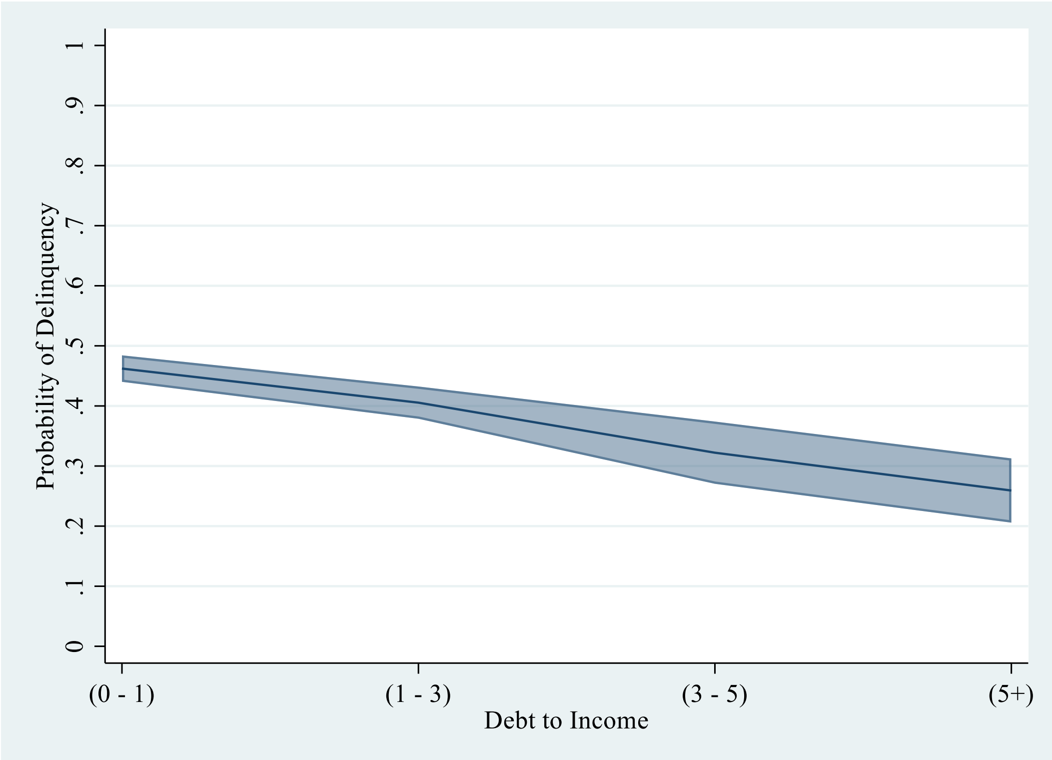
	Household income			
	6m	**12m**	**18m**	**24m**
Income	-0.0594**	-0.0751***	-0.0819***	-0.0971***
Debt to income				
(1 - 3)	-0.312***	-0.262***	-0.251***	-0.266***
(3 - 5)	-0.741***	-0.668***	-0.723***	-0.676***
(5+)	-1.049***	-1.007***	-0.947***	-0.825***
Female	-0.406***	-0.461***	-0.464***	-0.493***
Age	-0.0184***	-0.0204***	-0.0223***	-0.0254***
Number children	0.0699**	0.128***	0.155***	0.192***
Collateral	0.242***	0.497***	0.561***	0.543***
Observations	3654	3654	3654	3654
Mean dependent variable	0.246	0.404	0.455	0.499
AIC	3871.6	4477.6	4452.2	4344.2
BIC	4001.9	4607.9	4582.4	4474.5

* p<.1, ** p<.05, *** p<.01

Fixed effects on year of origination and location are included

The magnitude of the coefficients of the DTI variables can be seen in Figure 7, which shows the marginal effects. All the other variables are shown as means. It can be seen that changing DTI from (0 -1) to (5+) reduces the probability of delinquency by approximately 20 percentage points.

Figure 7: Marginal effect of initial DTI on delinquency after 12 months



5. Changes in DTI and delinquency over the loan cycle

This analysis estimates the effect of current DTI on the probability of delinquency. DTI is calculated for each month for which information is available and then related with the event of delinquency. To avoid endogeneity problems, we use lagged DTI values to estimate the probability of delinquency.

In the sample, 41% debtors have an average DTI higher than their initial DTI (Figure 8). As mentioned in Section 3, most of these changes are due to increases in debt (only the income of 5% of debtors in the sample decreased.[3] Figure 8 shows that many debtors have an initial DTI lower than 2 and have a much higher average DTI in the subsequent months.

[3] However, there could be debtors whose incomes decrease, but they are not accounted for in the survey (they were not surveyed in more than one year). For these debtors, we employed the income information available for one year and used the same value for the other years in which the debtors still had outstanding debt.

Figure 8: Average DTI versus Initial DTI

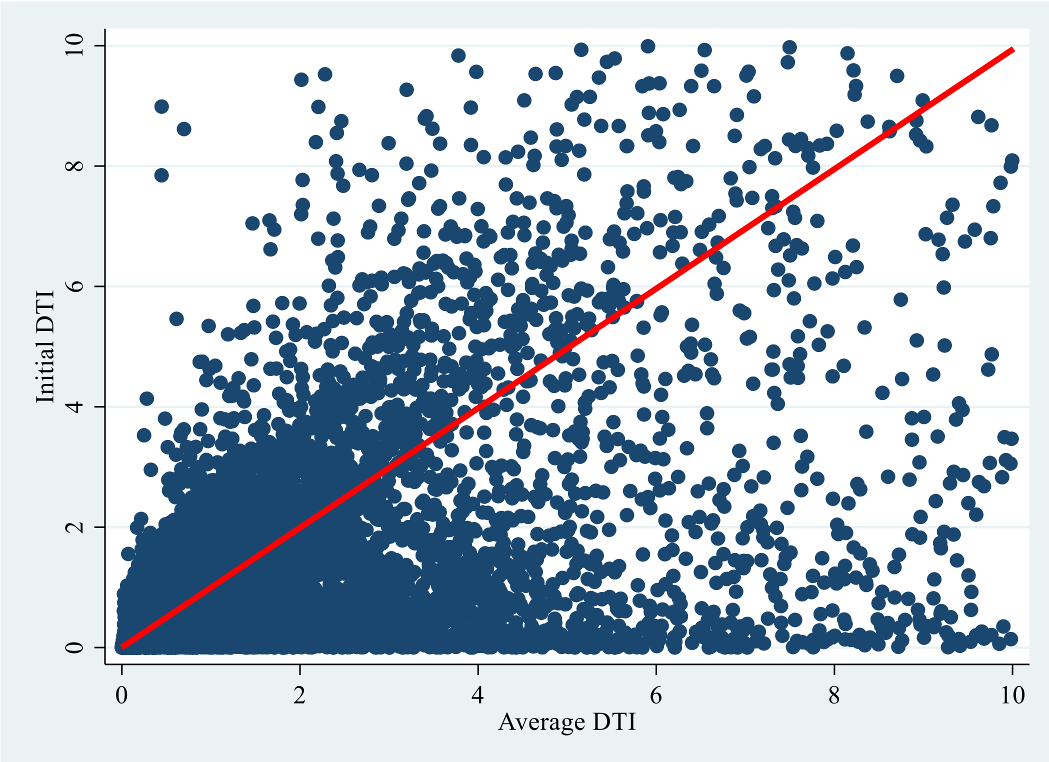
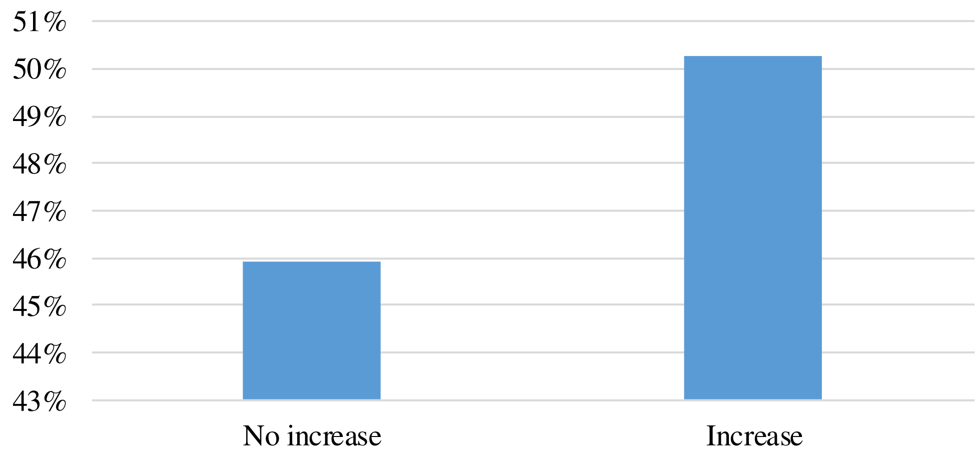


Figure 9 shows the delinquency of the group of people that increase their DTI and those who reduce it or keep it constant. The group that increase their DTI has higher percentage of delinquency than the group who did not (50.3% vs 45.9%). This first result show us that increments of the leverage of people are associated with higher delinquency.

Since there are other variables that are correlated with delinquency a multivariate panel data fixed effect model is estimated, this will help to find the pure effect of increments of DTI into the probability of delinquency. An advantage of this methodology is that it is robust to misspecifications at the individual level. If the unusual result is due to missing variables, this methodology will be robust to it.

Figure 9: Delinquency (%) by group of people that increase or not their DTI



5.1. Methodology

To evaluate the impact of DTI changes on the probability of delinquency, a logit fixed effect panel data is estimated. The fixed effect will allow to account for any missing variable at the individual level. In this setting, a variable is created that takes the value 1 whenever a debtor falls into delinquency and zero otherwise.[4]

5.2. Identification

The logit fixed effect panel data regression is as follows:

$$\Pr(delinquency)_{i,t} = \alpha_i + \beta DTI_{i,t} + \gamma X_{i,t} + \varepsilon_{i,t}$$

α_i: Fixed effect at the individual level
X_i: Income, Age, Number of bank relationships, Number of children

Table 4: Descriptive statistics of the variables - Analysis 2

Variable	Obs	Mean	Std. Dev.	Min	Max
Default dummy	263 460	0,11	0,31	0	1
Debt	263 460	4,06	6,44	0,1	104
Debt to Income (Hosehold)	263 460	1,74	2,10	1,12E-05	10
Household income (in S/000)	263 460	2,82	2,79	0,1	76
Banking relationship	263 460	1,52	0,88	1	8
Children	263 460	1,10	1,17	0	9

Table 4 shows that the percentage of delinquency is just 11% because, thanks to the panel data structure, many zero values before the event of delinquency are taken into

[4] It is worth mentioning that the permanence of a debtor in state of delinquency is high (71.2%).

account. However, the percentage of people that ever fall into default is 48.7%. From the debtors that ever fall into delinquency, 72.4% of them do so after one year.

As mentioned in Section 3, there is panel data information only for one thousand debtors. For that reason, the covariates income and number of children not always change for a single debtor. Therefore, a regression is estimated with all covariates and another one is estimated excluding these two variables.

5.3. Results

Table 5: Logit panel regression on delinquency

This table shows the estimates of a logit panel model where the dependent variable is *delinquency.*

	M1	M2
Income	0.0000307	
Debt to income		
(1 - 3)	-0.127***	-0.129***
(3 - 5)	0.144***	0.142***
(5+)	0.407***	0.410***
Number of bank relations		
2	0.875***	0.874***
3	1.480***	1.481***
Number children	-0.533***	
Observations	110332	110332
AIC	86785.1	86851.5
BIC	86852.4	86899.6

* p<.1, ** p<.05, *** p<.01

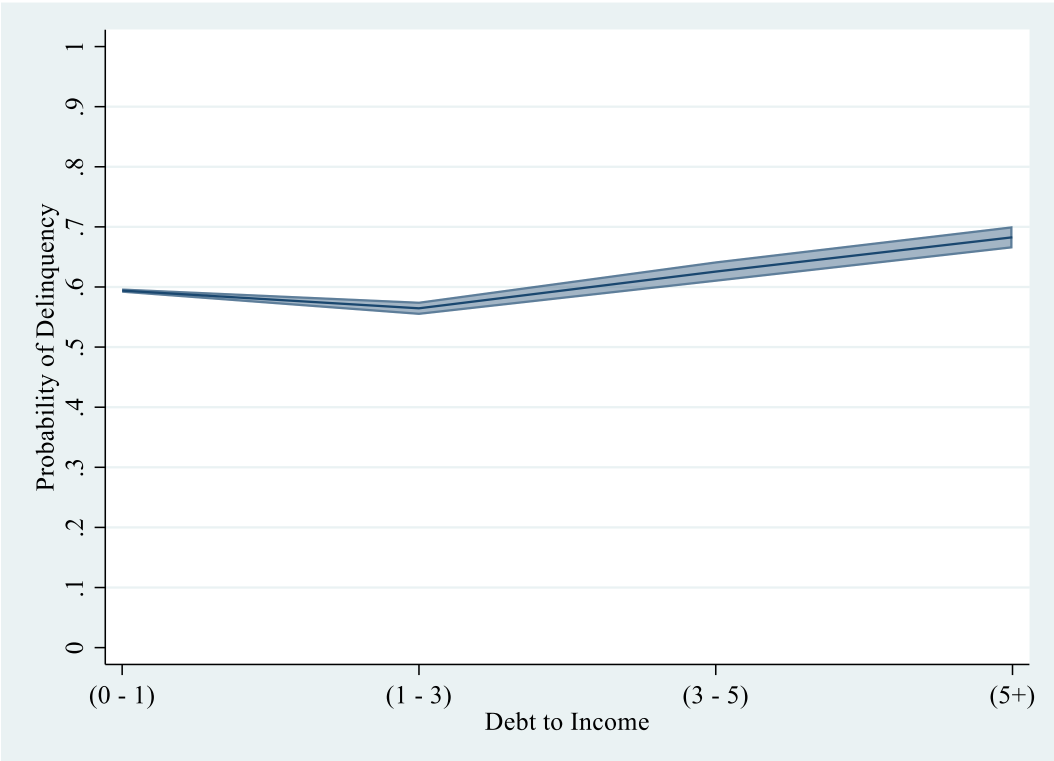
When excluding the covariates income and number of children, the other two variables, DTI and number of bank relations, do not change significantly.

In this estimation, the sign of the DTI variable is positive and the coefficient increases as DTI grows. This makes sense, since being more leveraged raises the credit risk. This shows that the evolution of the DTI variable is relevant to predict default. Furthermore, the number of bank relations is positive and significant, which is also related to increasing people's leverage.

Figure 10 shows that in this case, in contrast with analysis 1, the higher leverage corresponds to a higher probability of delinquency. In this case, changing from a DTI of (0 – 1) to (5+) increases the probability of default by approximately 0.10.

This shows that DTI is relevant as a surveillance variable, although its contribution is marginal and the analysis of credit risk should be accompanied by other relevant variables.

Figure 10: Marginal effect of lagged DTI on delinquency



Appendices 6 and 7 show the results using 120-day delinquency as dependent variable. Using this specification, DTI levels (3 – 5) and (5+) are not significantly different from (0 – 1). This suggests that DTI is better at predicting delinquency than default (120-day delinquency).

6. Conclusions

This paper discusses the importance of DTI, one of the most frequently used variables related to over-indebtedness for predicting delinquency. A unique dataset is built from a combination of Peru's credit registry and ENAHO data. The period of study is 2012-2017. Two types of analysis are used: a logit cross-sectional analysis for various periods and a logit fixed effect panel data model. These methodologies were used to analyze: i) the predictive power of DTI at origination; and ii) the predictive power of DTI in the period before the event of delinquency.

We find that leverage is not a good predictor of delinquency at origination. The results show a counterintuitive coefficient and a marginal effect, because it appears that higher leverage is associated with lower delinquency risk. The results may be influenced by missing variables, such as family wealth or debtors' financial loan neediness.

The second analysis shows that DTI changes matter in predicting delinquency. The signs of the coefficients become coherent; i.e., the model predicts that when debtors' leverage is higher, the risk of falling into delinquency grows. This methodology has the additional advantage of being robust to misspecifications at the individual level. Regarding the marginal effect, the predicted effect of a DTI change from (0 - 1) to (5+) is +0.1 of the probability of delinquency.

It is worth mentioning that this dataset was not build to be representative of all debtors. Instead, it was constructed by merging two datasets. For this reason, the results cannot be simply generalized. Nevertheless, they provide useful insights about the relevant relationships.

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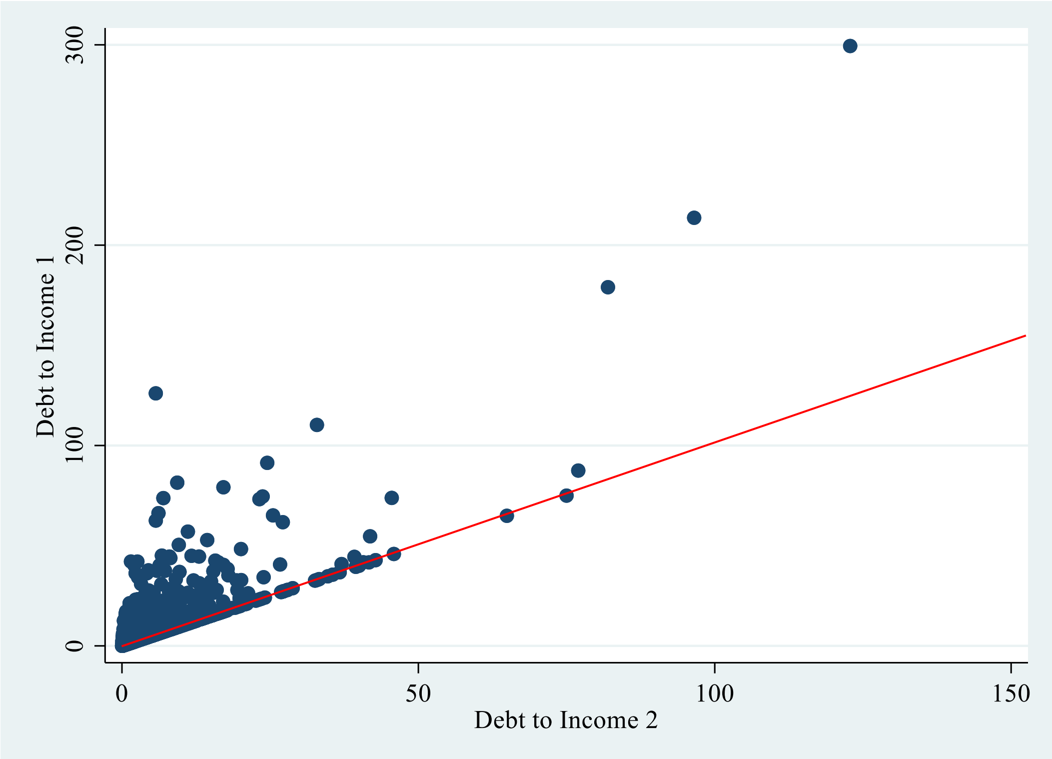
Appendix 1: Descriptive statistics of the variables

Variable	Definition	Source
Delinquency dummy	Indicator that takes 1 when a payment (of more than S/ 50) is in arrears for more than 30 days.	Credit registry
Debt (in S/000)	Outstanding debt of each debtor in thousand of soles	Credit registry
Debt to Income 1	Total outstanding debt over individual monthly income	Credit registry and household survey
Debt to Income 2	Total outstanding debt over household monthly income	Credit registry and household survey
Individual income (in S/000)	Monthly individual income in thousand of soles	Household survey
Household income (in S/000)	Monthly household income in thousand of soles	Household survey
Gender (Female=1)	Indicator variable that takes 1 when the debtors is female	Household survey
Age	Age of the debtor	Household survey
Banking relationship	Number of debts that the debtor has in different financial institutions	Credit registry
Children	Number of people below 15 years in the household	Household survey
Collateral	Indicator variable that takes 1 if the debtor has collateral of more than S/ 800	Credit registry

Appendix 2: Dispersion of debt to individual income and debt to household income



Appendix 3: Survival regression - Analysis 1

Income	-0.0565***
Debt to income	
(1 - 3)	-0.231***
(3 - 5)	-0.572***
(5+)	-0.817***
Female	-0.298***
Age	-0.0151***
Number of bank relations	
2	-0.468
Number children	0.0790***
Collateral	0.283***
Observations	3654
AIC	27204.0
BIC	27334.3

* p<.1, ** p<.05, *** p<.01

Fixed effects on year of origination and location are included

Appendix 4: Logit regression on delinquency for various time windows

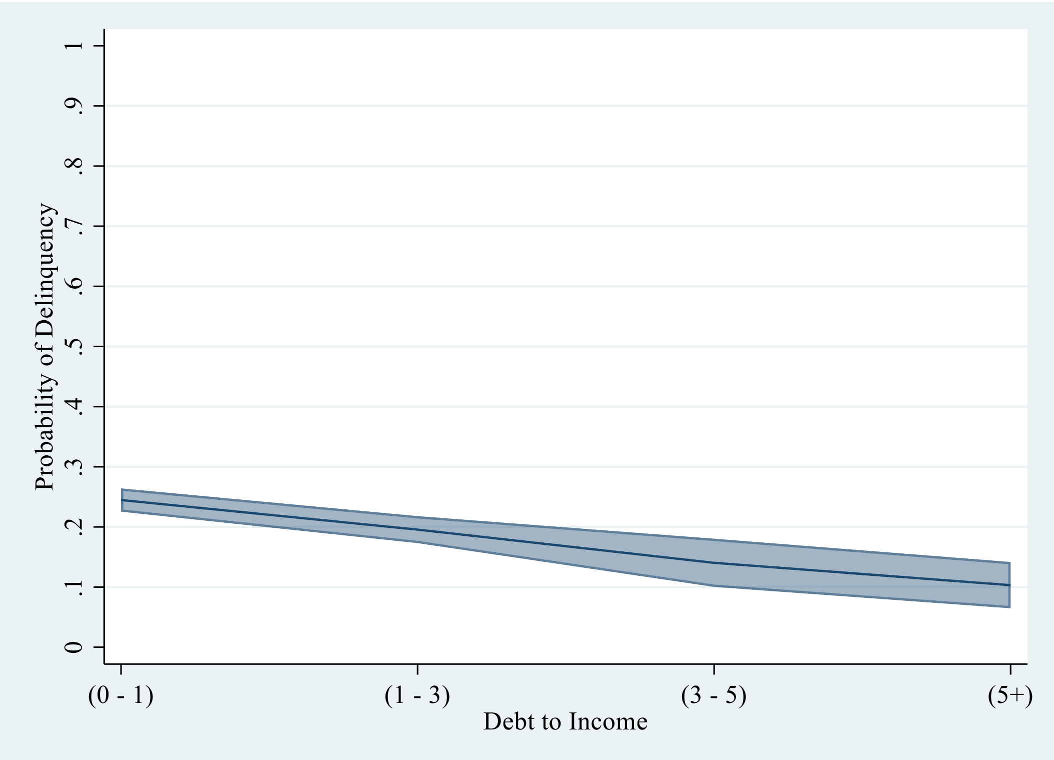
This table shows the estimates of a logit model where the dependent variable is *delinquency* for 120 days within different range of months after the loan origination.

	Household income			
	6m	**12m**	**18m**	**24m**
Income	-0.0648	-0.0458*	-0.0398	-0.0455*
Debt to income				
(1 - 3)	-0.461***	-0.310***	-0.179*	-0.147
(3 - 5)	-1.066***	-0.733***	-0.594***	-0.588***
(5+)	-0.641**	-1.099***	-0.656***	-0.528***
Female	-0.578***	-0.452***	-0.501***	-0.445***
Age	-0.0159***	-0.0209***	-0.0202***	-0.0205***
Number of bank relations				
2	0.181	0.0161	-0.363	-0.459
Number children	0.0278	0.0525*	0.0788***	0.0934***
Collateral	-0.216*	-0.0396	0.157*	0.183**
Observations	3477	3654	3654	3654
AIC	1932.6	3486.8	3931.8	4043.7
BIC	2061.8	3623.3	4068.3	4180.2

* p<.1, ** p<.05, *** p<.01

Fixed effects on year of origination and location are included

Appendix 5: Marginal effect of debt to income on delinquency for 120 days - Analysis 1



Appendix 6: Logit panel regression on delinquency for 120 days

This table shows the estimates of a logit panel model where the dependent variable is *delinquency* for 120 days.

	M1	M2
Income	-0.0000230	
Debt to income		
(1 - 3)	-0.325***	-0.330***
(3 - 5)	-0.0684	-0.0712
(5+)	0.117	0.116
Number of bank relations		
2	0.279***	0.274***
3	0.533***	0.529***
Number children	-0.815***	
Observations	73277	73277
AIC	38695.9	38758.2
BIC	38760.3	38804.2

* p<.1, ** p<.05, *** p<.01

Appendix 7: Marginal effect of debt to income on delinquency for 120 days - Analysis 2