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## Summary

Almost 10 percent of new non-mortgage borrowers experience payment problems within the first five months. Using data from Finansinspektionen's survey of new non-mortgage borrowers from 2019, this FI Analysis investigates why these borrowers experience problems. We use repeated payment reminders, collection notices, and claims from the Swedish Enforcement Authority to measure payment problems.

The probability of early payment problems decreases as the borrower's age increases. Similarly, the probability decreases if the borrower's income is high or the borrower has surplus discretionary income. The probability of experiencing problems appears to increase when interest and amortisation payments are large. In addition, more borrowers have problems when their credit service payments are high in relation to their income (debt service ratio). However, the debt service ratio's contribution to the payment problems is lower than the contribution of age, income and discretionary income.

We also find that a more in-depth credit assessment that includes information about existing loans reduces the probability that the borrower will experience payment problems.

Borrowers of small loans experience early payment problems more often than borrowers of large loans. This reflects that there is a link between the size of the loan and other important factors that affect the probability of payment problems, such as the borrower's income and the tendency of the credit provider to conduct a more extensive credit assessment. In general, the credit assessment for small loans is often less comprehensive. Our results show that when we control for the type of the loan and whether a credit assessment was conducted, the probability of payment problems increases as the size of the loan increases. Thus, all else equal, the risk of payment problems increases with the size of the loan.


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Table 1: Number of borrowers by type of new loan and type of credit provider

| Number of |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: |
|  | Unsecured loans | Non-propertybacked loans | Credit | Repayment |
| MB | 6,788 | 767 | 4,254 | - |
| SB | 10,312 | 2,750 | 16,200 | 4,977 |
| NPFC | - | 2,903 | 5,067 | - |
| CC | 731 | 550 | 21,034 | - |
| SFC | 264 | - | - | 212,362 |
| CCrl | 2,151 | - | 383 | 1,085 |
| Source: FI |  |  |  |  |
|  | Note: In total, 292,696 borrowers from Fl's consumer credit survey in 2019. |  |  |  |
|  | MB = major bank |  |  |  |
|  | SB = specialised bank |  |  |  |
|  | NPFC = non-property-backed financing company |  |  |  |
|  | CC = credit card company |  |  |  |
|  | SFC = sales financing company |  |  |  |
|  | $\mathrm{CCrI}=$ consumer credit institution |  |  |  |

## Loans can lead to payment problems

Swedish households' loans increased sharply during the 2000s (see Finansinspektionen, 2020b). This applies primarily to mortgages, but also to non-mortgage loans (unsecured loans, credit cards and lines of credit). Loans enable households to smooth out their consumption over time by consuming without first needing to save. Loans also make it possible to bridge periods of temporarily weaker finances (see Campbell et al., 2011). Loans can also cause problems for the borrower, though, since they tie up future income in interest and amortisation payments. If their financial situation weakens, it can be difficult for some borrowers to meet their financial obligations (see Meltzer, 2010).

Since loans can lead to payment problems, the Consumer Credit Act requires credit providers to assess whether the consumer is able to meet their loan payments (see Regeringen, 2010). This credit assessment is therefore an important part of consumer protection on the credit market, and promoting high consumer protection is one of Finansinspektionen's (FI's) assignments.

The objective of this FI Analysis is to explain why some borrowers experience payment problems. The analysis unfolds as follows. First, we describe the data we use to measure and explain payment problems. We then study how important the various explanatory factors are for understanding the payment problems.

## WE USE DATA ON NEW NON-MORTGAGE BORROWERS

We study why some borrowers experience payment problems using data from FI's survey of consumers with new non-mortgage loans. The most recent data is from May 2019 and contains information on 292,696 borrowers. ${ }^{1}$ Appendix A and Finansinspektionen (2020b) go into more detail on the dataset.

There are large differences between credit providers and products. FI therefore often breaks credit providers down into the following groups: major banks (MB), specialised banks (SB), non-propertybacked financing companies (NPFC), sales-based financing companies (SFC), credit card companies (CC) and consumer credit institutions (CCrI). ${ }^{2}$ We also broke the borrowers down by the type of their new non-mortgage loan: unsecured loans, non-property-backed loans, credit card/lines of credit, and interest-bearing instalment and invoice purchases (see Finansinspektionen, 2020b). Instalment and invoice purchases can be either interest-bearing at the time of purchase or convertible to an interest-bearing loan. Most invoice purchases do not entail a cost for the consumer. FI's survey includes only the instalment payments and invoices that entail a cost in addition to the cost of the good or service. Table 1 shows how the borrowers in FI's survey in 2019 break down into credit provider groups and credit types.

[^0]Table 2: Average income and loans broken down by type of credit provider Per cent and SEK

|  |  |  | Loans |  |
| :--- | :---: | :---: | :---: | :---: |
|  | Share | Income | New | Existing |
| MB | 4.0 | 36,224 | 78,306 | $1,071,681$ |
| SB | 11.7 | 32,544 | 54,041 | 892,760 |
| NPFC | 2.7 | 31,434 | 53,556 | $1,041,706$ |
| CC | 7.6 | 37,726 | 24,406 | $1,221,024$ |
| SFC | 72.7 | 25,504 | 1,455 | 805,410 |
| CCrl | 1.2 | 27,205 | 17,648 | 538,466 |
| All | 100.0 | 28,226 | 14,092 | 861,230 |
|  | Source: FI <br> Note: See the note to Table 1. Income refers to pre-tax <br> income. |  |  |  |

There are also differences between the borrowers of different company groups. The borrowers of sales-based financing companies and consumer credit institutions on average have lower income than other credit provider groups (Table 2). Borrowers of consumer credit institutions also have the smallest existing loans. This is because many of these borrowers do not have a mortgage or other large loans. The major banks and the credit card companies have customers with the highest income.

## PAYMENT PROBLEM MEASUREMENT

In this analysis, we use repeated payment reminders, collection notices, and demands from the Swedish Enforcement Authority as a measure of payment problems. Around 1 per cent of borrowers with a new non-mortgage loan receive a demand from the Swedish Enforcement Authority, almost 5 per cent receive a collection notice, and almost 7 per cent receive payment reminders within five months of the loan being paid out. ${ }^{3}$ In total, almost 10 per cent of new borrowers experience some kind of payment problem using one of these definitions.

We also conduct a sensitivity analysis where we use both a broader definition - including those who received one reminder - and a narrower definition - including those who only received a demand from the Swedish Enforcement Authority. All three definitions generate similar results, but the results in general are more articulated for the narrower definition (a demand from the Swedish Enforcement Agency). The advantage of the broader definition is that the results are based on a larger sample and thus are more statistically significant.

## Covariation between payment problems and plausible explanatory factors

Our dataset contains variables that can help explain why some borrowers experience early payment problems. Some explanatory factors - such as age and income - describe the borrower, and others are more linked to the credit provider - credit provider group, type of credit, and credit assessment scope. In addition, there is information about the size of new and existing loans, debt service payments (interest and amortisation), and ratios between the borrower's total loans and income (loan-to-income ratio) and service payment and income (debt service ratio). The most comprehensive explanatory factor we study is the discretionary income calculation. ${ }^{4}$

## WE CALCULATE ELEVATED PROBABILITY OF PAYMENT PROBLEMS

We begin by looking at simple correlations between payment problems and the explanatory factors. These correlations can give a

[^1]4 Appendix B provides information on our discretionary income calculation.

Diagram 1. Type of credit check by credit size Per cent


Source: FI
Note: Note: None refers to a credit assessment without a credit check, No credit exposure refers to credit checks without information about existing loans, and With credit exposure refers to credit checks with information about existing loans.

Diagram 2. Relative probability by type of credit check and size of loan (TSEK) Per cent


Source: FI

Diagram 3. Relative probability of payment problems by new loan (TSEK) Per cent


Source: FI
general indication of why some borrowers experience payment problems, but they do not show how important the factors are for explaining the problems. We will therefore also take the next step and analyse the correlations in so-called logistical models.

We study the simple correlations by breaking the new loans and borrowers down into groups based on the explanatory factors. We then calculate the share of the borrowers that had payment problems in each group and relate this share to the total share in the sample by calculating percentage deviations. If the share in a group is larger than in the sample as a whole, we say that the group has an elevated (relative) probability of experiencing payment problems. And if the share in a group is lower than in the sample as a whole, we interpret this to mean that the group has a reduced probability. ${ }^{5}$ We have chosen to report percentage deviation in a group compared to the entire sample since this corresponds to the information we get from the model estimates described later in this paper.

## SIMPLE CORRELATION BETWEEN FACTORS AND PAYMENT PROBLEMS

## Credit assessments appear to reduce the risk of payment problems

During a more comprehensive credit assessment, the credit provider runs a credit check that includes information about the borrower's existing loans. ${ }^{6}$ Credit checks that do not include credit exposure (without information about existing loans) are most common for small loans (Diagram 1). ${ }^{7}$ The percentage of checks that include credit exposure increases then with the size of the new loan.

The probability of experiencing payment problems is most elevated for borrowers who received a loan without the credit provider conducting any credit check at all (Diagram 2). ${ }^{8}$ Borrowers who received a loan with a credit check that did not include information about existing loans also have an elevated probability of experiencing payment problems - and in this case the probability increases with the size of the new loan. New loans preceded by a credit assessment that includes credit exposure had a 50 per cent reduced probability, regardless of the size of the loan.

[^2]

Source: FI
Note: Relative probabilities are calculated for only unsecured loans and non-property-backed loans.

Diagram 5. Relative probability of payment problems by maturity (year) Per cent


Source: FI
Note: Relative probabilities are calculated for only unsecured loans and non-property-backed loans.

Diagram 6. Relative probability of payment problems by age of borrower Per cent


Source: FI

## Small loans lead more often to payment problems than large loans

The simplest explanatory factor for payment problems is the size of the new loan. This data is always available when the loan is issued. Our results indicate that borrowers taking non-mortgage loans of less than SEK 5,000 have an elevated probability of experiencing payment problems (Diagram 3). One possible explanation for this is that the credit assessment is often less comprehensive for small loans than for large loans. Another possible explanation is that borrowers who take small loans often have smaller margins in their personal finances than those who take large loans since households with large margins do not need to take small loans. It can also be difficult for borrowers with low payment capacity to get large loans.

The next explanatory factor is the size of the borrower's existing loans. We see the same tendency for existing loans as for the new loan. Borrowers with existing loans of less than SEK 100,000 have an elevated probability of experiencing payment problems. This is because (relatively) small existing loans often consist of one or more smaller loans, where the credit assessment is not always comprehensive. It can also be because the borrowers with smaller existing loans have income that is clearly lower than the income of borrowers who borrowed more.

## Payment problems more common with high interest and short

 maturityCredit cards/lines of credit and invoice purchases often use standardised interest rates. They also often have a flexible rate of amortisation. This makes it difficult to analyse the interest and amortisation payments/maturity for these credit types. We therefore use the interest and maturity as explanatory factors only together with unsecured loans and non-property-backed loans. Loans with an interest rate of less than 5 per cent have a reduced probability of payment problems compared to more expensive unsecured loans and non-property-backed loans (Diagram 4). And an interest rate of more than 20 per cent results in a sharply elevated probability.

Borrowers who took a new unsecured or/// non-property-backed loan with a maturity of less than 2 years have an elevated probability of experiencing payment problems (Diagram 5). This is because the loans are small with high interest rates and, as mentioned above, small loans are correlated with payment problems. Loans with a maturity of more than 10 years (and in particular with an interest rate of more than 5 per cent) also have an elevated probability of payment problems.

## Low age and low income appear to increase probability of payment problems

The probability of early payment problems is clearly linked to the age of the borrower. Borrowers under the age of 25 have a 71 per cent higher probability of experiencing payment problems than borrowers on average (Diagram 6). Even borrowers between the ages of 25 and 34 have an elevated probability. The probability then decreases as the age increases.

Diagram 7. Relative probability of payment problems by borrower's post-tax income (TSEK/month)
Per cent


Source: FI

Diagram 8. Elevated relative probability of payment problems by loan-to-value ratio Per cent


Source: FI

Diagram 9. Elevated relative probability of payment problems by debt service ratio (total credit)
Per cent


Source: FI

Income is important since many borrowers use it for credit payments and subsistence costs. ${ }^{9}$ Borrowers with an income of less than SEK 10,000/month after tax have almost a 50 per cent higher probability of experiencing payment problems than the average (Diagram 7). Even those with an income between SEK 10,000-20,000/month demonstrate an elevated probability of payment problems.

## High debt service ratios appear to increase the probability of

 payment problems.We calculate the loan-to-income ratio as total loans divided by annual income after tax. ${ }^{10}$ Borrowers with low loan-to-income ratios have an elevated probability of experiencing payment problems at the same time as borrowers with higher loan-to-value ratios have a lower probability (Diagram 8). This can be a sign that those who need to take small loans experience payment problems more often than those who do not need to take small loans. When we look closer at borrowers with low loan-to-income ratios, we see that on average they have low income and small existing and new loans. Small loans can be expensive relative to their size due to high interest and amortisation. And, as we have already seen, the credit assessments can be less comprehensive for small loans and low income is an indication of payment problems.

It is not just the size of the loan that influences its impact on the borrower's finances. ${ }^{11}$ The type of credit is also important since different types of credit have different interest rates and rates of amortisation. The debt service ratio uses the same information as the loan-to-income ratio but also considers interest and amortisation. This means that the debt service ratio measures the percentage of post-tax income a borrower spends every month to pay for the loan. Borrowers spending more than 40 per cent of their post-tax income on debt service payments have an elevated probability of payment problems (Diagram 9). ${ }^{12}$

## Discretionary income deficit indicates payment problems

 Large deficits in our discretionary income calculation result in a clear increase in the probability of payment problems. A deficit of SEK 5,000 a month or more means a more than 50 per cent higher probability of experiencing payment problems compared to the average borrower (Diagram 10). Even borrowers with a smaller deficit in their discretionary income, or a small surplus, have an elevated probability. It is first borrowers with a surplus larger than SEK 5,000 in our discretionary income calculation who show a decreased probability of payment problems. These borrowers would also have had a surplus in the mortgage banks' discretionary income[^3]| Diagram 10. Elevated relative probability of payment problems by discretionary income Per cent |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
| $60 \square$ |  |  |  |  |  |
| 50 |  |  |  |  |  |
| 40 |  |  |  |  |  |
| 30 |  |  |  |  |  |
| 20 |  |  |  |  |  |
| 10 |  |  |  |  |  |
| 0 |  |  |  |  |  |
|  |  |  |  |  |  |
| -10 |  |  |  |  |  |
| -20 |  |  |  |  |  |
| -30 |  |  |  |  |  |
|  | $\begin{aligned} & \circ \\ & 80 \\ & \text { ị } \end{aligned}$ | $\begin{aligned} & \text { i } \\ & 1 \\ & 8 \\ & 0 \end{aligned}$ | $\begin{aligned} & 8 \\ & 0 \\ & 0 \\ & 0 \end{aligned}$ | 8 <br> 8 <br> 0 <br> 0 <br> 0 <br> $i$ | 응 <br> $\vdots$ <br> 1 |
|  | Source: FI |  |  |  |  |
| Table 3. Elevated relative probability by new credit type and credit provider group <br> Per cent |  |  |  |  |  |
| Credit provider | New loan |  |  |  |  |
|  | UL | NPBL | CCLC | Invinst | All |
| MB | -75 | -63 | -10 |  | -67 |
| SB | -47 | -50 | -43 | 88 | -21 |
| NPFC |  | -61 | -14 |  | -44 |
| CC | -67 | -39 | -65 |  | -64 |
| SFC |  |  |  | 8 | 8 |
| CCrl | 28 |  | 927 | -4 | 59 |
| All | -49 | -54 | -47 | 10 | 0 |

Source: FI
Note: A positive number means elevated probability of payment problems and a negative number means lower probability.

Note:
UL = unsecured loan
NPBL = non-property-backed loan
CCLC = credit card or lines of credit
InvInst $=$ Invoice or instalment
Also see the note to Table 1.
calculations, which are much stricter than our calculations (see Finansinspektionen, 2020c).

Many borrowers with large deficits in the discretionary income calculation do not appear to experience payment problems. One explanation is that we only measure payment problems that occur within five months of pay-out of the new loan. Another explanation could be that our calculation does not perfectly illustrate the borrower's finances. It is therefore important to distinguish between a discretionary income deficit and not having enough money to pay for expenses. For example, being able to use a loan to maintain consumption following a temporary fall in income can be positive for the borrower.

Differences between credit provider groups and credit types Consumers with new interest-bearing invoices and instalments experience payment problems more often than other borrowers (Table 3). This applies in particular to instalments from a specialised bank. Unsecured loans, non-property-backed loans and credit cards/lines of credit show in general a 50 per cent lower probability of payment problems. Differences between credit types can be due to differences in the credit assessment. For example, invoice purchases are exempt from the credit assessment requirements (see Regeringen, 2010).

There are also differences between credit provider groups and the different credit types. Customers of consumer credit institutions have a notably higher probability of payment problems than other customers. This applies in particular to credit cards and credit lines but also to unsecured loans. These differences may be due to the varying comprehensiveness of the credit assessments conducted by each credit provider. These differences can also be partly explained by variations in the income of the credit provider groups' customers as well as other differences in the credit providers' business models.

## What are the payment problems due to?

So far, we have studied simple correlations between plausible explanatory factors for and measures of payment problems. There can be strong correlations between explanatory factors, which means that several factors could capture the same dimension of payment problems. For example, we find a strong positive correlation between the borrower's income and discretionary income (Table D2 in Appendix D). This is because income is an important component of the discretionary income calculation. The borrower's existing loans are also related to the loan-to-income ratio and to some extent to the debt service ratio. Income is also related to the ratios, which is not surprising given how the ratios are calculated. We are also seeing strong correlation between non-property-backed loans and non-property-backed financing companies, between credit cards/credit lines and credit card companies, and between invoice purchases and sales-based financing companies.

In order to be able to identify which explanatory factors are the most important for the probability of payment problems, we therefore go one step further in this section. This analysis consists of logistic regressions that estimate the probability of payment problems given
the explanatory factors. ${ }^{13}$ The models enable us to understand each factor's relative significance for some borrowers experiencing payment problems. The models contain both quantitative and category variables. ${ }^{14}$ We have standardised all of the quantitative variables. ${ }^{15}$ This means we can compare how much an increase in one standard deviation of each explanatory factor influences the probability of payment problems. ${ }^{16}$ A corresponding interpretation of the category variables shows how much the probability of payment problems in each category deviates from a reference category. Tables 4-6 below show the results where we include variables that are statistically significant at the $5 \%$ level.

## FACTORS EXPLAIN ONLY PART OF THE PROBABILITY OF PAYMENT PROBLEMS

The above review of the explanatory factors shows that no individual factor can provide a perfect illustration of whether the borrower will experience payment problems. There can also be other explanations for why the borrower experiences payment problems, such as earlier payment problems or more comprehensive information about the origin of the income data. Unfortunately, we do not have access to this information (and a lot of other information). It is also possible that life events are important for explaining payment problems, for example unemployment, illness and divorce. These events are largely unknown for both the credit provider and the borrower at the time the loan is granted. It is also possible that debts and expenses other than loans are the main cause of the payment problems. Regardless of the reason, our estimates show that it is not possible to assess with full accuracy at the point in time when loan is issued whether the borrower will experience payment problems. However, the models do provide information about which of our factors contribute to the explanation for the payment problems.

## AGE, INCOME AND DISCRETIONARY INCOME GIVE THE MOST USEFUL INFORMATION ABOUT THE BORROWER

Strong correlation between income and discretionary income means that when one of them is included in the model, the other does not contribute anything to the explanation. We included income in the basic model for the borrower assessment (see "Basic Model" in Table 4). ${ }^{17}$ Variables that describe credit types, credit provider groups and credit assessment are modelled separately later. The size of the loan is also included in the later models. ${ }^{18}$

The age of the borrower affects the probability of experiencing payment problems the most of all the variables. When age increases by one standard deviation - which corresponds to 14 years - the

[^4]probability falls by approximately 22 per cent. The second-most important borrower characteristic is income (or discretionary income, depending on which of the two variables we choose to include in the model). The probability of payment problems decreases by around 12 per cent when income increases by one standard deviation (SEK 9,700).

The model shows that a low age means elevated probability of payment problems even when considering the borrower's income. Furthermore, we see in the data that borrowers older than 64 have a lower probability and young borrowers an elevated probability, regardless of income. This could be because the finances of young borrowers are more uncertain - income is most likely not as stable for young adults - but it could also be because they are not as experienced at handling bills and expenses.

Since the debt service ratio is not correlated with income (or discretionary income), it contributes extra information. When the debt service ratio increases by one standard deviation (16 percentage points), the probability of payment problems increases by 9 per cent.

The model furthermore shows that the probability of payment problems decreases by 20 per cent when the loan's maturity increases by one standard deviation ( 24 months). One explanation for this could be that longer maturities mean lower monthly amortisation payments, which in turn allows for a larger margin in the borrower's finances. Just like in the review of the simple correlations, the estimates indicate that the probability of payment problems decreases as the loan-toincome ratio increases.

We estimated an additional two variations of the model to test the robustness of our results. In the first, we excluded the borrower's age (Without age). Without the age variable, the contribution from income was almost twice as large as in the basic model. Other effects were approximately the same. In the second, we only included borrowers who received a demand from the Swedish Enforcement Authority as the dependent variable (Only SEA). In this model, the contribution from income is half as large as in the basic model, but the maturity is more important. When the maturity increases by one standard deviation in this alternative model, the probability of the borrower receiving a demand from the Swedish Enforcement Authority falls by 90 per cent.

We can interpret the difference between the basic model, with our measure of payment problems, and the alternative model, with borrowers who received a payment injunction from the Swedish Enforcement Authority, as degrees of payment problems. The borrower's age has approximately the same impact on both measures. This indicates that age is equally important for borrowers who experienced more serious payment problems than for those with other payment problems. Income is less important, and the maturity is significantly more important for those who received a demand from the Swedish Enforcement Authority.

Table 4. Difference in odds ratio for estimated models of the borrower
Per cent

|  | Basic model | Without age | Only SEA |
| :--- | :---: | :---: | :---: |
| Age | -22.3 |  | -25.0 |
| Income | -12.3 | -21.0 | -3.5 |
| Maturity | -20.2 | -20.5 | -88.9 |
| Loan-to-income ratio | -7.2 | -11.5 | -3.9 |
| Debt service ratio | 8.9 | 8.2 | 4.0 |

Source: FI.
Note: In the basic model, we use our measure of payment problems as the dependent variable. The difference in the odds ratio shows how the probability of payment problems changes when the explanatory variable increases by one standard deviation. "Without age" means a model without age, and "Only SEA" means only those who received a demand from the Swedish Enforcement Authority are included in the dependent variable.

In order to refine the importance of the explanatory factors, we use a single credit type - unsecured loans - and estimate separate models for major banks, specialised banks, and consumer credit institutions. Major banks issue larger unsecured loans that often have a low interest rate to borrowers with higher income (Table 2). Consumer credit institutions issue smaller loans that often have high interest rates to borrowers with lower income. The specialised banks' interest rate and the income of their borrowers falls between the other two credit provider groups. The probability of payment problems is lowest among those who take an unsecured loan from a major bank -1.3 per cent. Corresponding probabilities for customers at specialised banks and consumer credit institutions are 4.9 and 16.7, respectively.

Young borrowers have an elevated probability of experiencing payment problems within each credit provider group. The probability decreases by between 26 and 46 per cent when the borrower's age increases by one standard deviation - 14 years (see Table 5).

The borrower's income and credit service ratio explain differences in payment problems when we consider all unsecured loans. However, the differences are not statistically significant within each credit provider group. This indicates that income and the debt service ratio (through the credit assessment) affect whether or not the credit provider will grant a loan. The major banks' business model appears to result in them issuing loans to the borrowers with the strongest payment capacity. Borrowers with the smallest margins normally borrow from a consumer credit institution since they often cannot get a loan from a major bank.

Overall, the maturity has only a small impact on the probability of a borrower with a new unsecured loan experiencing payment problems. However, the probability of payment problems increases by 20 per cent when the maturity increases by one standard deviation (24 months) for customers at a major bank. For borrowers at consumer credit institutions, the probability decreases by 20 per cent when the maturity increases by 24 months. It is worth noting that 20 per cent means different things in the two groups - the probability of payment problems increases to 1.6 per cent for customers of major banks and
decreases to 13.4 per cent for borrowers at consumer credit institutions. ${ }^{19}$

Table 5. Difference in odds ratio for borrowers taking unsecured loans by credit provider group

Per cent

|  | All | MB | SB | CCrI |
| :---: | :---: | :---: | :---: | :---: |
| Age | -38.2 | -31.0 | -46.6 | -26.0 |
| Income | -10.6 |  |  |  |
| Maturity | -2.6 | 21.7 |  | -19.3 |
| Debt service ratio | 12.7 |  |  |  |

Source: FI.
Note: The difference in the odds ratio shows how the probability of payment problems changes when the explanatory variable increases by one standard deviation.

## CLEAR DIFFERENCES BETWEEN CREDIT PROVIDER GROUPS

Unsecured loans are small or large and have different interest rates and maturities, which are set in the loan agreement. Non-propertybacked loans are similar to unsecured loans, but they are often large. Credit and interest-bearing invoice purchases often have standardised interest rates and flexible rates of amortisation. Another difference between the credit types is that the probability of a borrower experiencing payment problems varies. Around 3 per cent of borrowers who took an unsecured loan or a non-property-backed loan experience payment problems. The corresponding percentage for those who used credit card or credit lines or made a purchase on instalments or by invoice is 12 per cent. Due to the differences between the credit types, we estimate two models: one for unsecured loans and non-property-backed loans and another for credit and interest-bearing invoice purchases.

The difference between unsecured loans and non-property-backed loans is not statistically significant. ${ }^{20}$ But there are differences between credit provider groups. Borrowers in all other credit provider groups have a higher probability of experiencing payment problems than those borrowing from a major bank (Table 6). Borrowers taking a loan from a consumer credit institution have the highest probability. The effects of the different credit provider groups are not statistically significant in the model. This is because of the strong correlations between the credit provider group and the credit type. The probability of payment problems increases by almost 60 per cent when the loan's interest rate increases by one standard deviation ( 9 percentage points). This is most likely because higher interest expenses lead to small margins for the borrower. Credit providers also offer lower interest rates to borrowers they assess to have a lower risk of payment problems and thus a lower risk of credit losses. The probability

[^5]increases to some extent even with the size of the loan. The loans that were preceded by a credit check with information about existing loans demonstrate a 33 per cent lower probability of payment problems than other loans. This supports the assertion that the more comprehensive the credit assessment the lower the share of borrowers with payment problems.

For those using credit cards, lines of credit, payment instalments or invoices, the probability of payment problems increases with the size of the loan (Table 6). The contribution of the credit type is not statistically significant in this model, either. And, like in the model for unsecured and non-property-backed loans, this is most likely due to strong correlations between credit provider groups and credit types. Differences between the credit provider groups can be interpreted as those using credit cards or lines of credit having a lower probability of payment problems than those making an interest-bearing purchase via invoice. The highest probability of payment problems is associated with those who use interest-bearing invoices from sales-based financing companies for payment, and the lowest probability is associated with those using credit from a credit card company. This could be because borrowers with credit cards or lines of credit have higher income than borrowers buying on instalment plans or by invoices.

The simple correlation shows that the probability of payment problems decreases with the size of the new loan (Diagram 3). When we control for the credit provider group, credit type and whether the credit provider uses a credit check with information about existing loans, the correlations reverses - then the probability increases with the size of the new loan. This means that, all else equal, the risk of payment problems increases with the size of the loan.

Table 6. Difference in odds ratio for estimated models on loans and credit providers///

Per cent

|  | Unsecured <br> loans and non- <br> property- <br> backed loans |  | Credit and <br> invoices |
| :--- | :---: | :--- | :---: |
| Size of new loan | 4.9 | Size of new loan | 17.9 |
| Nominal interest <br> rate | 58.1 |  |  |
| MB (Unsecured, | Ref | MB (Credit) | -24.2 |
| NPB) | 80.7 | SB (Credit) | -16.6 |
| SB (Unsecured, <br> NPB) | 62.1 | NPFC (Credit) | -26.6 |
| NPFC (NPB) |  | CC (Credit) | -72.1 |
|   SFC Ref <br> CCrl <br> (Unsecured) -33.1   <br> Information on <br> existing loans    <br> Soures)    |  |  |  |

Source: FI.
Note: Parenthetical text refers to the company's primary lending. The difference in the odds ratio shows how the probability of payment problems changes when the explanatory variable increases by one standard deviation. MB=major bank, $\mathrm{SB}=$ specialised bank, NPFC=non-property-backed financing company, $\mathrm{CC}=$ credit card company, SFC = sales financing company, and $\mathrm{CCr}=$ consumer credit institution. Major banks are the reference in the model for unsecured loans and non-property-backed loans. Major banks (unsecured loans and non-property-backed loans) are the reference in the model for unsecured loans and non-property-backed loans. Sales-based financing companies (invoices) are the reference in the model for credit and invoices.

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Table A1: Percentage in the survey with information about income and existing loans Per cent

| Inc. | Mortgage | Unsecured <br> loans | Non- <br> property- <br> backed <br> loans |  |
| :--- | :---: | :---: | :---: | :---: |
| MB | 98 | 75 | 74 | 63 |
| SB | 93 | 48 | 63 | 51 |
| NPFC | 100 | 40 | 40 | 40 |
| CC | 100 | 99 | 99 | 99 |
| SFC | 77 | 0 | 1 | 1 |
| CCrl | 93 | 19 | 38 | 13 |
| All | 82 | 17 | 19 | 17 |
|  |  |  |  |  |

Source: FI
Note: It is not known who issued the existing loans. The information comes from Fl's consumer credit surveys. Inc. = income.
$M B=$ the new loan is from a major bank
SB = specialised bank
NPBFC = non-property-backed financing company
CC = credit card company
SFC = sales-based financing company
$\mathrm{CCrI}=$ consumer credit institution

## Appendix A. New data for total loans

In the analysis, we use data from FI's survey of consumer credit from 2019. The survey includes income data for 82 per cent of the borrowers (see Table A1). For those who have not reported income, we generated an income using statistical methods. We divided the borrowers into groups by age, size of the new loan, and the credit provider group from which they took the new loan. There are borrowers that have a (reported or generated) income that is lower than social assistance. We have raised the income of these borrowers to the same level as social assistance.

We also generated existing loans for those missing this data. The existing loans consists of mortgages, unsecured loans, credit cards and lines of credit, and non-property-backed loans. The method we use means that the generated data is well in line with the borrowers that have this data. The generated data are primarily used in the analysis of existing loans and discretionary income.

Income
We broke the borrowers down into groups by

- Age
- Size of the new loan (new)
- Company type (comp)

Given these groups, we broke the borrowers down into those with information about income and those without:

$$
\begin{gathered}
I^{\text {has }}=I \mid G_{\text {age }}, G_{n e w}, G_{\text {comp }}, I \geq 0 \\
I^{\text {miss }}=I \mid G_{\text {age }}, G_{n e w}, G_{\text {comp }}, I \text { missing }
\end{gathered}
$$

We assigned every $I^{\text {miss }}$ a randomly drawn value from $I^{\text {has }}$ through sampling with replacement. This procedure - which is similar to a bootstrap - uses the empirical probability distribution and generates the expected distribution asymptomatically. ${ }^{21}$ In other words, the correct percentage with 0 in income and the correct distribution for other borrowers if the sample is large enough.

## Existing loans

In this case, we divided the borrowers into groups by

- Income (including those with sampled income)
- Age group
- Size of the new loan
- Company type

1. Given these groups, we broke the credit variables down into (with the notation $L_{j}$, where $j=$ loan type)
a. $\quad L_{j}^{\text {has }}=L_{j} \mid G_{\text {inc }}, G_{\text {age }}, G_{n e w}, G_{\text {comp }}, L_{j} \geq 0$
b. $\quad L_{j}^{\text {miss }}=L_{j} \mid G_{i n c}, G_{\text {age }}, G_{\text {new }}, G_{\text {comp }}, L_{j} m i s s i n g$
[^6]Table A2. Percentage of married broken down by mortgage (MSEK) and the sum of unsecured loans and non-property-backed loans (SEK 100,000) Percentage

| Percentage |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Unsecured loans and <br> Non-propertybacked loans |  | Mortgages (MSEK) |  |  |  |  |
|  |  | 0-1 | 1-2 | 2-3 | 3-5 | $>5$ |
| 0-4 |  | 0.33 | 0.47 | 0.55 | 0.64 | 0.77 |
| 4-6 |  | 0.40 | 0.58 | 0.58 | 0.77 | 0.83 |
| >6 |  | 0.60 | 0.74 | 0.75 | 0.78 | 0.95 |
| Source: FI |  |  |  |  |  |  |
| Diagram A1. Percentage of borrowers with existing loans by credit type and company type <br> Per cent |  |  |  |  |  |  |
|  |  |  |  |  |  |  |

2. We assigned every $L_{j}^{\text {miss }}$ a randomly drawn value from $L_{j}^{\text {has }}$. We drew the value in the same was as for the sampled income.
3. We used the procedure for:
a. Total mortgages
b. Total unsecured loans
c. Total loans with other collateral
d. Total utilised credit cards and lines of credit
4. We calculated the total credit (for those whose did not have this information) as the sum of the credit types.
5. For borrowers where we did have information about total credit but not on the credit types, we sampled the credit types (point 3). We then scaled the credit types so their total (total credit) matches the reported figure. If such a borrower received 0 in all credit types, we distributed the total credit using average distribution of the subaggregate for the company type that issued the new loan in question.

Under this method, we assumed that those without information about income or loan follow the same distributions as those for which we have information (given our groupings).

## Existing loans and co-signers

Often, a single person takes a non-mortgage loan. Around 98.5 per cent of the borrowers in the consumer credit survey in 2019 had no co-signer for the new loan. But 98.5 per cent of the borrowers were not single-family households. We have information about the marital status of approximately 40,000 borrowers. And among these, 39 per cent were married. Unmarried can also have a shared economy, but we use their characteristics to identify single-person borrowers. The reason that we used marital status is that this is the information we have access to (for a limited number of households). We used the percentage of married broken down by size of mortgage and the sum of unsecured loans and non-property-backed loans. The percentage increased in both dimensions (Table A2). Using the percentages, we randomly draw co-signers for all borrowers in the surveys. We draw from the Bernoulli distribution with conditional probabilities from Table 2.

We also made the simplified assumption that borrowers who have cosigners pay half of the interest and amortisation for existing loans.

Persons with new consumer credit from a major bank, specialised bank, non-property-backed financing company or credit card company already had a mortgage in 60 per cent of the cases (Diagram A1). The percentage was lower for customers at sales-based financing companies and, in particular, consumer credit institutions. The percentage of customers that had existing unsecured loans and credit cards was largest at the sales-based financing companies. Consistently, the percentage of customers with existing loans was lowest at the consumer credit institutions.

## Appendix B. Discretionary income calculation, assumptions and standardisations

One of our indicators is a simplified discretionary income calculation. It uses the borrower's post-tax income, which we calculated in accordance with the calculations of the Ministry of Finance. From income, we deduct debt service payments (interest after tax deductions and amortisation), standardised subsistence costs (that here are only dependent on how many adults and children live in the household), and housing costs (that here are only dependent on whether the borrower lives in owned or rented accommodation). According to the Bill to the Consumer Credit Act, the credit provider must obtain a comprehensive overview of the consumer's financial situation when granting a loan (see Regeringen, 2010). We set subsistence costs at the Swedish Enforcement Authority's normal amount, which serves as a basis for wage-distraint and debt restructuring. These are lower than the Swedish Consumer Agency's and the mortgage banks' standardised costs and can be interpreted as a subsistence minimum. ${ }^{22}$

Discretionary income calculations estimate the borrowers' cash flows, but they cannot capture the exact situation in reality. Borrowers can have payments that are lower or higher than the standardised amounts we use. In addition, borrowers can have savings that they can use if their financial circumstances deteriorate. Then it also matters if there are one or two people who have the loans. In the material, we know if the new loan has one or two borrowers. To determine the number of borrowers on existing loans, we started with marital status (Appendix A). Those with co-signers have lower subsistence and housing costs per person.

We are aware that some loans may be included in subsistence costs since goods and services can be purchased on invoice and with instalments instead of paying for them immediately. However, we have still chosen to include interest-bearing invoices and instalment purchases as payments in addition to subsistence costs, in part because all credits in the sample have imposed a cost on the borrowers, for example by being interest-bearing. In addition, they will impact the borrower's finances in the future.

Table B1 shows the values we use in the discretionary income calculation. We also use some values for the debt service ratio.

[^7]Table B1. Standardised costs, interest rates and maturities

| Magnitude |  | Interest | Amortisation |
| :---: | :---: | :---: | :---: |
| Mortgage |  | 1.6\% | 50 years |
| Unsecured loans | Major bank | 5\% |  |
|  | Specialised bank | 7\% |  |
|  | Consumer credit institution | 10\% |  |
|  | Unsecured loan < SEK 100,000 |  | 6 years |
|  | Unsecured loan SEK 100,000350,000 |  | 9 years |
|  | Unsecured loan > SEK 350,000 |  | 12 years |
| Non-propertybacked loan |  | 3.5\% | 6 years |
| Credit cards |  | 15\% | 1/24 |
| Expenses | SEK/Month |  |  |
| 1 adult | 5,900 | Including tr | el expenses |
| 2 adults | 10,100 | Including tr | el expenses |
| Children | 3,000 |  |  |
| Rental apartment | 6,000 | Those in th not have a | surveys who do ortgage |
| Owned housing | 3,500 | Those in th have a mo | surveys who age |

Source: FI and the Swedish Enforcement Authority.

## Appendix C. Countries with restrictions on debt service ratios

Table C1. European countries with restrictions on debt service ratios

| Country | Threshold | Restriction | Scope |
| :---: | :---: | :---: | :---: |
| Cyprus | 80 per cent | Bind. | All credit providers |
| Estonia | 50 per cent | Bind. | All credit providers |
| Lithuania | 40 per cent | Bind. | All credit providers |
|  | 50 per cent <br> (5 pp interest |  |  |
| Netherlands | Depends on income and interest | Bind. | All credit providers |
| Poland | 40 per cent | Rec. | Banks |
|  | (inc<average) |  |  |
|  | 50 per cent |  |  |
|  | (other) |  |  |
| Portugal | 50 per cent | Rec. | All credit providers |
| Romania | 40 per cent | Bind. | All credit providers |
| Slovakia | 80 per cent | Bind. | All credit providers |
| Slovenia |  | Rec. | Banks |
|  | (Depending on income) |  |  |
| Czechia | 45 per cent | Rec. | All credit providers |
| Hungary | 25-60 per cent | Bind. | All credit providers |
| Austria | 30-40 per cent | Rec. | All credit providers |

Source: ESRB.

Note: Rec. $=$ recommendation and Bind. $=$ binding regulation.

Table D1. Mean and standard deviation for quantitative variables.
Year, SEK, per cent, months, SEK, per cent, per cent, and SEK

|  | Mean | Std |
| :--- | :---: | :---: |
| Age | 41 | 14 |
| New loan | 11,400 | 4,500 |
| Interest (nom) | 7.9 | 9.0 |
| Maturity | 12.1 | 24.8 |
| Income (net) | 21,200 | 9,700 |
| Loan-to-income <br> ratio | 237 | 322 |
| Debt service ratio 18 16 <br> Discretionary <br> income 8,000 9,500 |  |  |

## Source: FI

## Appendix D. Estimate of marginal effects.

The main article presents how different factors influence the probability that a borrower experiences payment problems.

The explanatory variables consist of both continuous variables - age, income, size of loan, loan-to-income ratio, debt service ratio, and discretionary income - and dummy variables. We standardised the continuous variables by deducting the mean and dividing by the standard deviation. This means that the variable increases by one standard deviation when it goes from 0 to 1 (Table E1). The dummy variables are constructed so that each unique value in a category is assigned its own variable with the value 1 in the category to which it belongs and the value 0 in other categories. For example, if a borrower has taken a new non-property-backed loan, the borrower is assigned the value 1 in the dummy variable Non-property-backed Loan and the value 0 in the other credit type variables. In order for the equation not to be overidentified, we have excluded the categories Unsecured Loans and Major Banks. Borrowers included in these categories will be included in the model's constant term and serve as a reference for the other categories.

CORRELATIONS BETWEEN EXPLANATORY VARIABLES
Table D2. Correlations between quantitative variables
\(\left.$$
\begin{array}{lllllll}\hline & \text { Y } & \text { NL } & \text { I } & \text { B } & \text { SK } & \text { LBK }\end{array}
$$ \begin{array}{c}Disc <br>
inc <br>

calc\end{array}\right]\)| Age | 1.00 |  |  |  |  |
| :--- | :--- | :--- | :--- | :--- | :--- |
| New loan | 0.05 | 1.00 |  |  |  |
| Income | 0.31 | 0.11 | 1.00 |  |  |
| Existing <br> loan | 0.13 | 0.04 | 0.42 | 1.00 |  |
| Debt serv <br> ratio | 0.08 | 0.04 | 0.10 | 0.82 | 1.00 |

Source: FI

Table D3. Correlations between category variables

|  | Unsecured <br> loans | Non- <br> property- <br> backed <br> loans | Credit | Invoice |
| :--- | :--- | :--- | :--- | :--- |
| Unsecured <br> loans | 1.00 | -0.03 | -0.08 | -0.50 |
| Non- <br> property- <br> backed <br> loans | -0.03 | 1.00 | -0.05 | -0.32 |
| Credit | -0.08 | -0.05 | 1.00 | -0.74 |
| Invoice | -0.50 | -0.32 | -0.74 | 1.00 |
| MB | 0.51 | 0.04 | 0.01 | -0.31 |
| SB | 0.35 | 0.19 | 0.39 | -0.58 |
| NPBFC | -0.03 | 0.47 | 0.09 | -0.24 |
| Missing info | 0.01 | 0.00 | 0.05 | -0.04 |
| CC | -0.05 | 0.03 | 0.65 | -0.51 |
| SFC | -0.47 | -0.30 | -0.68 | 0.93 |
| CCrl | 0.22 | -0.01 | -0.02 | -0.11 |
| CAFrower | 0.00 | 0.00 | 0.06 | -0.05 |
|  | 0.29 | -0.01 | 0.08 | -0.23 |
|  | 0.39 | -0.32 | 0.67 | -0.89 |
| CAF |  |  |  |  |
|  |  |  |  |  |

Source: FI
Note: CAF = credit assessment from firms and IB = information from borrower.

## LOGISTICAL REGRESSIONS FOR PROBABILITIES

The logistical regression assumes the dependent variable values 0 and 1. In our case, 0 means that the borrower did not experience payment
problems and 1 that the borrower did experience problems. The equations have the functional form

$$
\begin{equation*}
L_{i, \tau}=\ln \left(\frac{P}{1-p}\right)=\alpha+\beta^{\prime} X+\varphi^{\prime} D+u_{i} \tag{D1}
\end{equation*}
$$

where $P$ is the probability that a borrower will experience payment problems. $\alpha, \beta$ och $\varphi$ are parameters, and $u_{i}$ is a random term. $X$ are continuous variables and $D$ dummy variables.

Given the estimated equations, we can calculate the probability that a borrower will experience payment problems using

$$
\begin{equation*}
\hat{P}=\frac{1}{1+e^{-\hat{L}}} \tag{D2}
\end{equation*}
$$

We also calculate odds ratios. They assume that all variables in $X$ and $D$ are equal to 0 , which is the denominator in the calculation. In the ratio's numerator, we allow one of the variables (at a time) to assume the value 1 . The odds ratio then shows how much the variable influences the probability of payment problems. In line with other calculations, we account for how large the relative increase is in per cent.

Table D4. Estimated models.

| Basic model borrowers |  | Unsecured loans and non-property-backed loans |  | Credit and invoices |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Constant | $\begin{gathered} \hline-2.31 \\ (0.007) \end{gathered}$ | Constant | $\begin{gathered} \hline-3.26 \\ (0.102) \end{gathered}$ | Constant | $\begin{gathered} \hline-2.11 \\ (0.013) \end{gathered}$ |
| Age | $\begin{gathered} \hline-0.25 \\ (0.008) \end{gathered}$ | New loan, size | $\begin{gathered} 0.05 \\ (0.012) \end{gathered}$ | New loan, size | $\begin{gathered} \hline 0.16 \\ (0.048) \end{gathered}$ |
| Income | $\begin{gathered} \hline-0.13 \\ (0.008) \end{gathered}$ | Nominal interest rate | $\begin{gathered} \hline 0.46 \\ (0.051) \end{gathered}$ |  |  |
| Maturity | $\begin{gathered} \hline-0.23 \\ (0.010) \end{gathered}$ | MB |  | MB | $\begin{gathered} \hline-0.28 \\ (0.145) \end{gathered}$ |
| Loan-toincome ratio | $\begin{gathered} \hline-0.07 \\ (0.008) \end{gathered}$ | SB | $\begin{gathered} \hline 0.59 \\ (0.097) \end{gathered}$ | SB | $\begin{gathered} \hline-0.18 \\ (0.029) \end{gathered}$ |
| LBK | $\begin{gathered} 0.09 \\ (0.008) \end{gathered}$ | NPBFC | $\begin{gathered} 0.48 \\ (0.149) \end{gathered}$ | NPBFC | $\begin{gathered} -0.31 \\ (0.109) \end{gathered}$ |
|  |  |  |  | CC | $\begin{gathered} \hline-1.28 \\ (0.052) \end{gathered}$ |
|  |  |  |  | SFC |  |
|  |  | CCrl | $\begin{gathered} 0.88 \\ (0.163) \end{gathered}$ |  |  |
|  |  | Information on existing loans | $\begin{gathered} \hline-0.40 \\ (0.091) \end{gathered}$ |  |  |

## Source: FI

Note: The table shows estimated parameters, and the parenthetical figure specifies the standard error of the estimate.


[^0]:    1 We removed observations that contained outlier values for income, number of children, and number of co-signers. We also need information about payment problems for borrowers. The number of borrowers therefore differs from the number in Finansinspektionen (2020b).
    2 Finansinspektionen (2020b) provides a detailed description of the credit provider groups.

[^1]:    3 FI has information about this for 91 per cent of borrowers with new non-mortgage loans. For credit cards and lines of credit, the lead time is ten months. Different credit providers have different routines for when they send payment reminders and collection notices. We have not taken this into consideration in this analysis. One reminder can be a sign of temporary payment problems but can also be a sign of inattention or a decision by the borrower to delay the payment. However, multiple reminders on the same loan are a first indication of recurring payment problems.

[^2]:    5 For example, if 12 per cent of a group of borrowers have payment problems according to our definition, this is 20 per cent more than among all borrowers, which is the outcome of our payment problem measure. The calculation in the example looks like this: 12 per cent in the group have payment problems and 10 per cent in the sample have payment problems.

    Relative probability $=100 \times(12-10) / 10$.
    6 Credit providers can buy credit checks. A credit check can contain, for example, information about the borrower's income, loans, and any record of non-payment.
    However, a credit check does not necessarily include all loans that a consumer has since not all credit providers report information about loans to (all) credit reference firms.
    7 There are different credit checks that include credit exposure. The credit check that a credit provider uses depends on what it reports in or chooses to pay for. Some credit exposures include all reported loans while others only include a specific type of loan, for example unsecured loans.

    8 The results show that a credit assessment that does not include a credit check has a reduced risk if the loan is between SEK 20,000 and SEK 50,000 . The results are generated by a small number of borrowers - 95 .

[^3]:    9 The borrower may have savings that can be used for debt service payments. The borrower may also receive help (temporarily or permanently) from another person to pay off the loan, such as parents.

    10 The loan-to-income ratio can also be calculated using pre-tax income. We have chosen post tax to make the calculation comparable to other indicators in this FI Analysis.
    11 If we had studied only a single homogeneous type of credit - with similar interest rates and amortisation - the loan-to-income ratio would have been more informative as an indicator. For example, this applies to mortgages.

    12 Forty per cent is close to what many other countries use as their recommendation or regulation. See Appendix C.

[^4]:    13 The results from the logistical regressions cannot necessarily be compared to the results from the simple correlations.

    14 The category variables are defined as the value 1 if the borrower belongs to the category; otherwise, the value is 0 . The category variables are often called dummy variables.
    15 Standardised variables are constructed so that they have an average of zero and a standard deviation of one. With standardised variables, we can directly compare parameter estimates.
    16 Table D1 of Appendix D gives the mean and standard deviation for the quantitative variables.

    17 When both income and discretionary income are included in the model, the discretionary income variable is not statistically significant.
    18 Table D4 in Appendix D shows the estimated models.

[^5]:    19 The differences are because, at the outset, the probability of payment problems is 1.3 per cent for the customers of major banks and 16.8 per cent for customers at consumer credit institutions.

    20 In the model for unsecured and non-property bank loans, unsecured loans are the reference against which other credit types are compared.

[^6]:    21 See Efron and Tibshirani (1994) for a description of bootstrap methods.

[^7]:    22 The Swedish Consumer Agency's standards are based on what they consider to be reasonable consumption. We used the Swedish Enforcement Authority's normal amount so as not to be interpreted that we were making a recommendation.

