WHO BORROWS AND WHO MAY NOT REPAY?

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Abstract

We use Household Budget Survey data to analyze the evolution of the household credit market in the Czech Republic over the period 2000–2008. We next merge our data with the Statistics on Income and Living Conditions in 2005–2008, in order to test the validity of the standard debt burden measure as a predictor of default. We propose an alternative indicator – the adjusted debt burden (ADB), defined as the ratio of loan repayments to discretionary income, constructed as net income minus the living minimum, which turns out to be a superior predictor of default risk. Limited by the data, we use a fairly broad concept of default, namely, the inability to make loan repayments on time. Based on the distribution of default risk across the levels of the adjusted debt burden, we suggest that a 30% ADB threshold should be used as the definition of overindebtedness, with an average default risk of 17%. Finally, we show that overindebtedness and local economic shocks are closely related, suggesting that default risk should be always considered in the context of regional economic conditions.

Abstrakt

Studie využívá dat ze Statistik rodinných účtů k analýze vývoje trhu spotřebitelských půjček domácnostem v České republice v období 2000-2008. V dalším kroku pomocí dat z Výběrových šetření příjmů a životních podmínek z období 2005-2008 analyzujeme, jak dokáže standardní indikátor dluhového břemene předpovídat default. V souvislosti s tím navrhujeme alternativní indikátor: upravené dluhové břemeno (UDB), které definujeme jako poměr úvěrových splátek k disponibilnímu příjmu, tj. čistému příjmu domácností po odečtení životního minima. Ukazuje se, že tento alternativní indikátor předpovídá default lépe než standardní indikátor dluhového břemene. Vzhledem k tomu, jaké informace jsou v datech k dispozici, definujeme default poměrně široce jako neschopnost zaplatit úvěrové splátky ve stanoveném termínu. Na základě rozdělení rizika defaultu přes různé úrovně upraveného dluhové břemene navrhujeme klasifikovat domácnosti s UDB vyšším než 30 procent jako příliš zadlužené; tyto domácnosti mají 17 procentní riziko defaultu podle naší definice. V závěru poukazujeme na úzkou souvislost mezi lokální přílišnou zadlužeností a místními ekonomickými šoky a doporučujeme, aby analýza agregátního rizika defaultu brala v úvahu regionální variaci v zadluženosti, a to s ohledem na regionální ekonomické podmínky.

JEL codes: D12, D14, G21, R29
Key words: household credit, debt burden, repayment, regional default risk

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**Czech National Bank

1. Introduction

The most frequently used measures of household borrowing are based on aggregate data and aggregate indicators, such as the total amount of credit extended to households or the average debt burden for the whole population. However, only household-level analysis using micro data can reveal the actual concentration of debt in the population and can help identify households that are overindebted and whose repayment ability is the most likely to be affected by negative economic shocks, which is crucial for the evaluation of default risk and for financial stability analysis. Only a very few papers, such as Zochowski and Zajaczkowski (2006) and Faruqui (2008), who use Polish and Canadian household budget surveys, respectively, inspect household indebtedness at the micro level and present the distribution of the debt burden in a population. Furthermore, in the same country context as our analysis, Jakubik and Schmieder (2008) show that aggregate default models work reasonably well for the corporate sector but usually fail to explain household sector default, suggesting again that aggregate measures of household debt are not sufficient.

The aim of this paper is to analyze the evolution of the household credit market in the Czech Republic over the last decade and to assess its default risks. Following the single-country studies mentioned above, this paper is the first to use Czech household-level data on borrowing and default to complement the existing aggregate figures of the Czech household credit market.[1] The first part of the analysis is based on data from the Czech Household Budget Survey (HBS), an annual cross-sectional survey conducted by the Czech Statistical Office, over the period 2000–2008. We analyze the evolution of different types of household loans and identify the key determinants of household borrowing. While the percentage of households with at least one loan remained rather stable and below 40% over the given period, the composition of household credit by types of loans changed as the credit market for housing loans expanded relative to the market for consumer loans. The average size of new loans increased over the period analyzed, with a sharp rise during the housing market boom in 2007 and a drop during the financial crisis in 2008. We estimate a series of probit and tobit regressions of the determinants of a household's probability of having a loan, its probability of taking out a new loan, the amount of the new loans taken out, and the level of the debt burden. The typical household that borrows the most has young members who are employees, have higher income, have children, live in a city, and have been married for a shorter period of time. They are also less risk averse and have experience with financial products.

As the share of households that borrow remained stable, the expansion of the credit market through growth in the size of loans points to gradual debt accumulation among households. On average, about 18% of households with an existing loan are granted a new loan each year. Having an existing loan is also an important positive determinant of getting a new loan in our regression analysis, in particular for the years after the credit bureau was established and information-sharing started to be used in the Czech Republic. As loan accumulation increases households' degree of indebtedness, we analyze the level, distribution, and determinants of

[1] For research into the Czech household credit market based on aggregate data, see, for example, Pašaličová and Stiller (2004).

the debt burden of households using the standard definition of the debt burden[2] (DB), i.e., the ratio of annual loan repayments to annual net income. The distribution of the debt burden among households that borrow moved towards higher levels over the analyzed period, starting with the majority of households concentrated below the level of 10% in 2000, with a median equal to 4.5%, to almost half of the population crossing this level in 2008, with a median debt burden of about 9%. The level rose in particular among young households with higher income levels, pointing to expansion of the housing loan market as being the main source of the increase of the debt burden. In addition, we propose an alternative definition of debt burden, the so-called *adjusted debt burden* (ADB), which takes into account the variation in the costs of living across households of different size and composition. Specifically, we define the ADB as the ratio of yearly loan repayments to *discretional* yearly income, constructed as net income minus the household-type-specific living minimum as set by the Czech Statistical Office. Similar to the DB measure, the median ADB also increased over the analyzed period, starting at 9.3% in 2000 and ending at 14% in 2008.

Besides describing the households that borrow and the rising level of their debt burden, we augment our analysis with a complementary dataset – the Statistics on Income and Living Conditions (SILC) – for the period 2005–2008, with information on households' repayment difficulties and delayed payments. Based on the only information available in our data, we define default as the inability to make loan repayments on time. This is our definition of default throughout this paper. As only a fraction of households with delayed payments eventually default on their loan obligations, our measure of the default risk is very conservative.

As a debt burden above a certain ad-hoc level, such as 40 or 50%, is often used as a measure of a household's overindebtedness and a signal of default (see, for example, Willeke, 2009), we explore the correlation between our two debt burden measures and the occurrence of delayed repayments in order to compare their predictive power and identify the data-driven cut-off point above which default is likely. As the HBS data includes detailed information on borrowing but no information about default, and the SILC data contains the opposite, we use the HBS data to estimate a model of loan repayments based on households' socio-economic characteristics and income (present in both datasets) and use this model to predict loan repayments in the SILC data. With the predicted annual loan repayments and the actual annual net income, we construct the debt burden measure for each household in the SILC data and analyze the relationship between the debt burden and default. We find that the relationship is not strong enough to make the standard debt burden definition a satisfactory indicator of the risk of default.

We show that the ADB is correlated twice as strongly with the default rate as the standard DB indicator. Furthermore, we find that households with a DB above 15% and with a ADB above 30% are substantially more likely to default on their payments, which is why we propose these two levels as the cut-off points for overindebtedness, corresponding to an

[2] While the literature sometimes refers to the ratio of total debt outstanding to income as the debt burden, we use the more frequently used definition of the debt burden as debt service.

average default risk of 10% and 14% in 2008. Based on our definition of overindebtedness, and reweighting the HBS data to represent the whole population, we conclude that overindebted households accounted for about 40% of repayments made and 33% of new loans taken out in 2007. This corresponds to 7% of total repayments and 6% of total new loans in 2007 being at risk of default.

Finally, as one of the first microdata studies of the household credit market, we explore regional differences in household borrowing.[3] We find that the share of households that borrow and their indebtedness vary substantially across regions in the Czech Republic and are positively correlated with each other as well as with local economic conditions, in particular unemployment. The degree of indebtedness and default across regions are also strongly positively correlated and confirm the validity of the ADB as a signal of default also at the regional level. We also show that the negative impact of the 2008 financial crisis in 2009 was bigger in regions with a higher initial share of overindebted households in 2008.

This paper is organized as follows. The next section briefly summarizes the literature and the key measures of household indebtedness, including our proposed ADB measure. The section which follows describes the evolution of the household credit market in the Czech Republic over the last decade at the aggregate level and using household level data. The fourth section presents our estimation results from the analysis of the determinants of household borrowing. The fifth section focuses on the repayment behavior of households; we compare the standard debt burden and the proposed ADB measure, identify an ADB threshold of 30% as a signal of overindebtedness, and simulate the share of overindebted households in loan repayments and new loans. The sixth section focuses on regional differences in borrowing and overindebtedness and their relation to the regional variation of economic shocks. The last section concludes. Additional estimation outputs, data details, and prediction evaluations are included in the Appendix.

2. Literature Review and Key Concepts

2.1. Previous Research

Default in the household credit market is typically a consequence of negative macroeconomic shocks, such as a reduction in income or job loss. Households that have accumulated a higher amount of debt relative to their regular income sources are more likely to be unable to repay their loans. This is why a measure of household indebtedness is a crucial indicator for the prediction of default. Jappelli et al. (2008) show that household default is more sensitive to macroeconomic shocks in countries with higher household indebtedness, but that the sensitivity also depends on institutional factors.

3 For example, Vandone (2007) suggests that, in addition to the variation of debt across income and household socio-economic characteristics, there are substantial geographic differences in the demand for consumer credit.

Most empirical research into household borrowing focuses on the question of whether household debt has grown so much as to impede households' ability to service their debt and therefore constitutes a threat to financial stability. For example, Girouard et al. (2006) analyze household debt in several OECD countries between 1980 and 2005 and conclude that the rise in household borrowing can be mainly attributed to favorable economic conditions and the boom in the housing market. They also inspect the distribution of debt across different income levels and find that most of the debt was accumulated by higher-income households, for whom servicing the debt is relatively easy.

The most popular measures of the household debt burden are the ratios of household debt to GDP, household debt to disposable income (net of taxes), household debt service (total loan repayments) to disposable income, and household debt to financial assets, as well as the household delinquency rate and the personal bankruptcy rate. Garner (1996) provides an overview of several of these aggregate indicators and assesses their ability to predict the economic slowdown in the U.S. over the period 1961–1996. These measures are often either based on aggregate-level data or averaged over the population.

However, as mentioned in the introduction, such indicators cannot capture the concentration of debt among households. For example, the average debt service burden ratio for the whole population is jointly determined by the share of households with outstanding debt and the amount of the loan repayments of households with outstanding debt. It is crucial for financial stability concerns, as well as for monetary policy, to disentangle these two factors that jointly determine the reported average debt burden.[4] The use of microdata is therefore crucial for the analysis of household indebtedness, as it can provide measures of debt concentration and, in particular, reveal the distribution of the debt burden among households in the population. The most popular indicator in the few microdata studies available is the ratio of loan repayments to disposable income, i.e., what we call – and use in this paper as – the debt burden indicator. See, for example, Faruqui (2008), Hellebrandt et al. (2008), Girouard et al. (2006), or Zochowski and Zajaczkowski (2006).

Dynan et al. (2003) propose an alternative measure to what we call the debt burden – the so-called financial obligations ratio, which adds recurring obligations to total loan repayments in the numerator of the debt burden. The debt burden is then the ratio of the total financial obligations of a household, including both loan repayments and recurring fixed obligatory expenses such as rent, auto leases, homeowners' insurance, and property taxes, to disposable income. This measure is, in its logic, the closest measure to our ADB indicator that we found in the literature. Specifically, it is similar in that it also takes into account other household expenses. In this case, however, the expenses are those which households are obliged to pay regularly to other parties, whereas in our definition they are those which households necessarily incur in order to maintain some minimum standard of living.

[4] The risk of default threatening financial stability in a population of households that all borrow but have a moderate debt burden is very different from the risk of default in a population where only half of the households borrow but they have twice as high a debt burden. However, the average debt burden indicators are the same under the two scenarios.

2.2. Key Concepts – Debt Burden Measures

It is important to clarify the terminology. *Debt burden* is sometimes defined as the ratio of total debt to disposable income (income net of taxes), whereas the ratio of repayments to disposable income is called the *debt service burden*. However, according to the dictionary definitions, the debt burden is the cost of servicing debt. It follows that the debt burden ratio is the ratio of the debt burden to disposable income, which is the definition we use throughout this paper, although for brevity we drop the word "ratio" and refer to the concept as the debt burden.

In our analysis, we first use this standard definition of debt burden (DB), specifically in our data the ratio of the annual amount of loan repayments in the given year to household disposable annual income. We then propose an alternative measure, the *adjusted debt burden* (ADB), which as the denominator uses households' "true" discretionary income rather than disposable income, taking into account the household's minimum necessary expenses. We construct the adjusted debt burden as the ratio of the amount of loan repayments in the given year to annual household income net of the household-type-specific *living minimum*. The living minimum is the minimum annual expenditure of a household of a given size and composition, as set by the Czech Statistical Office.[5] While the DB tells us what proportion of annual income a household uses to service its debt, the ADB tells us the proportion of discretionary annual income a household pays out in loan repayments.

The DB is calculated in exactly the same way for households of all sizes and compositions, regardless of the fact that discretionary income, i.e., income available for loan repayments in the event of financial distress, varies substantially across different household sizes. Consider two different households – one a single-member household who works and the other a household with one working adult, one adult not working, and two children. It may well be the case that the two households have the same total annual loan repayments and the same total disposable income. In the event of financial distress (say as a result of a negative economic shock), the first household can use for loan repayments all income up to the minimum expenditure necessary for one person, whereas the second household is left with a smaller amount of income after subtracting the minimum necessary for its four members. The two household types have identical DBs, but the second household is likely to encounter repayment difficulties at much lower DB levels than the first household. The DB measure does not reflect the difference in the default risk between these two households, while the ADB measure does. The ADB of the second household is much higher than that of the first, given the higher minimum expenditure of the four-member household compared to the one-member household. Furthermore, in terms of the evolution of indebtedness over time, the DB – in contrast to the ADB – does not capture the effect of the evolution of prices if it differs from that of household income.

In this sense, the ADB is a preferable measure for comparing a household's ability to service debt over time. For example, if prices go up but disposable income stagnates, the ability of a

5 The calculation of the living minimum can be found in section B in the Appendix.

household to service debt diminishes. This is correctly captured by a rise in the ADB, in contrast to the DB, which does not change in this scenario. Thus, the ADB can well explain higher default rates and consequently possible threats to financial stability in periods of recession, when growth in the total debt decreases. This scenario is illustrated, for example, in Hellebrandt et al. (2008), where the authors report that although the distribution of debt did not change much in Britain in 2008, the average household found it more difficult to service its existing debt due to higher prices and consequently lower discretionary income. As we show later in this paper, the ADB turns out to be a better predictor of default than the DB in the cross-sectional dimension as well.

On the other hand, the DB requires only two pieces of information: total loan repayments and income net of taxes, which are typically available and well defined for international comparison purposes. The ADB, however, requires additional information about the minimum costs that the household incurs to decently survive. The currently used living minimum is only the first step towards a possibly refined concept of minimum costs. It varies only by household size and composition, which is already an improvement over the DB, which does not take into account even this minimum source of heterogeneity across households. However, the costs of living vary also with other characteristics, such as home-ownership status and region of residence. Interestingly, Beck et al. (2010), who use SILC data for a number of old and new EU member states to analyze the determinants of access to mortgages, also compare the self-reported financial distress and vulnerability of mortgage owners versus renters and outright owners and find no difference between these groups.

While we expect that using a refined measure of household costs in the ADB calculation will further increase the predictive power of the ADB, the downside, on the other hand, is the need to correctly measure the additional information on minimum expenditures and their comparability across households. Unless it is well and simply defined, such a refined ADB concept is likely to have limited application outside the national environment and common institutional settings (such as rent regulations). The development of an adequate but easily implementable concept of household costs for ADB calculations at the international level is a subject for future research.

3. Household Credit Market Trends

3.1. Aggregate Perspective

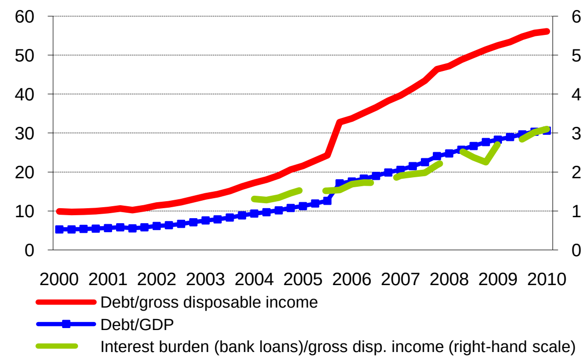
Household debt in the Czech Republic has grown substantially in the last several years (see Figure 3.1). On the aggregate level, the loans-to-GDP ratio reached 31% in 2009.[6] Household indebtedness as measured by the ratio of loans to gross disposable income averaged across all households in the population also increased, reaching 56% in 2009. Since the escalation of the global financial and economic crisis, annual growth in loans to households has slowed significantly, reflecting changes in both demand and supply side factors. On the other hand,

6 The indicators of household indebtedness comprise loans provided by both banks and non-banks since 2006.

the ratios of debt to GDP and to gross disposable income have continued to increase owing to the fall in economic activity and the deterioration in the labor market.

Relatively low interest rates have kept the increase in household debt service contained, despite the rise in indebtedness. However, the average debt (service) burden in the whole population has increased over the period analyzed, reaching (on loans from banking institutions) around 3%.[7] This reflects the past evolution of interest rates on loans and the long-term rise in households' debt.

Figure 3.1: Ratios of household debt to gross disposable income and GDP (%)



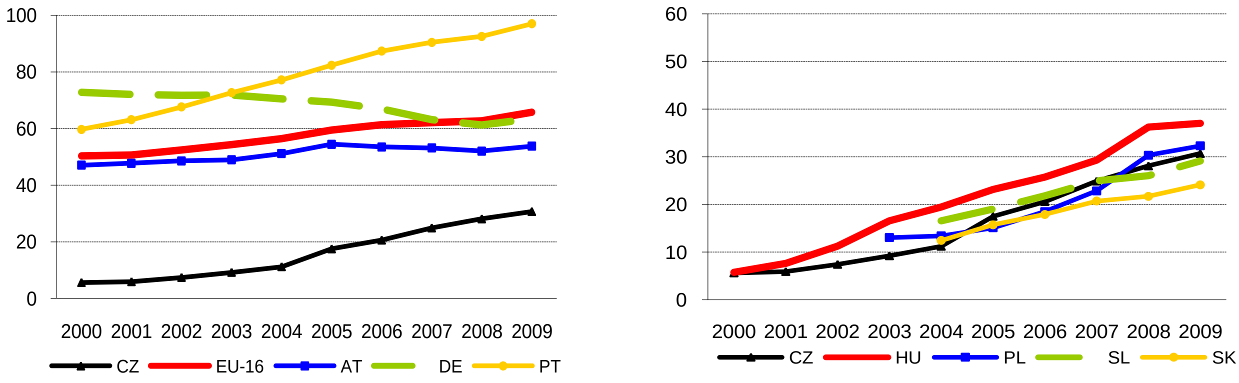
Source: CNB. Debt is the total household debt to banking institutions between 2000 and 2005. Household debt to non-banking institutions is also included since 2006. The interest burden pertains to loans from banking institutions only.

The previous acceleration of credit growth in the Czech Republic raises the question of whether the loan growth rate in Czech Republic was excessive or not. A comparison of the situation in the Czech Republic with that in other EU and CEE countries (see Figure 3.2) reveals that the loans-to-GDP ratio in the Czech Republic is lower than that in the euro area[8] and is broadly comparable to that in other countries of the Central European region. However, it is likely that private sector indebtedness in the Czech Republic is still below its long-term equilibrium level.

7 Note that as this debt burden measure is averaged across all households (including those that do not borrow) and only includes loan repayments for loans from banking institutions, it is not directly comparable with the household-level-based DB measure which we use throughout this paper.

8 The higher indebtedness in the euro area might also be due to the excess debt in some European countries (for example Portugal).

Figure 3.2: Household loans-to-GDP ratio in the international context (%)



Source: CNB

The aggregate evolution of the economy and household loans in terms of growth rates and base interest rates are documented in Figures 3.3 and 3.4. Various factors account for the household credit market growth (and in particular the growth in housing loans), which peaked in 2005 and 2007: decreasing interest rates on loans, income and population growth, and past deregulation and liberalization, which broadened the range of both mortgage loan suppliers and loan products.[9] However, the severe recession following the failure of Lehman Brothers in September 2008 put the financial position of households under considerable strain; the credit conditions tightened and many homeowners saw their housing equity eroded. While GDP and gross disposable income increased over much of the analyzed period, the trend reversed in 2007 and the two values dropped in 2009. Unemployment was steadily decreasing until 2008 but then rose significantly as a consequence of the financial crisis.

Figure 3.3: Loans, income and unemployment rate (real annual growth, %)

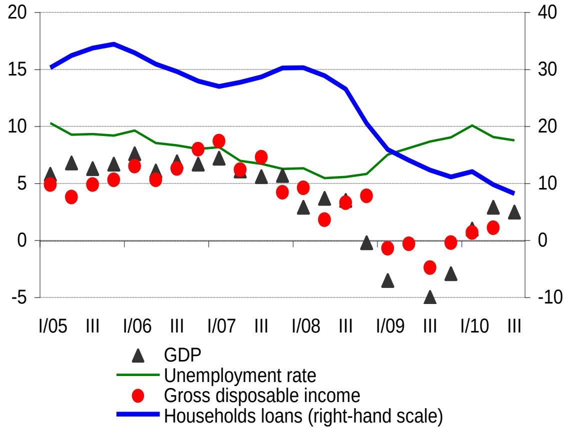
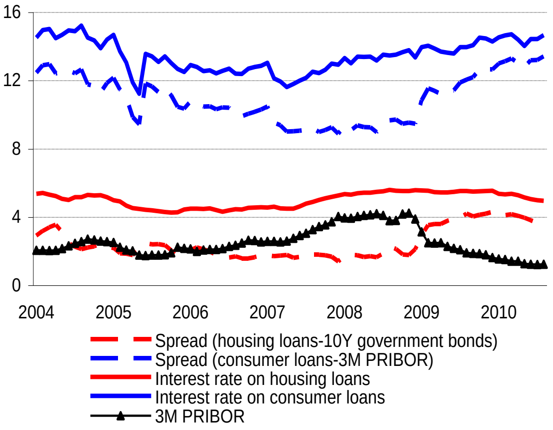


Figure 3.4: Client interest rates and spreads (%, p.p.)

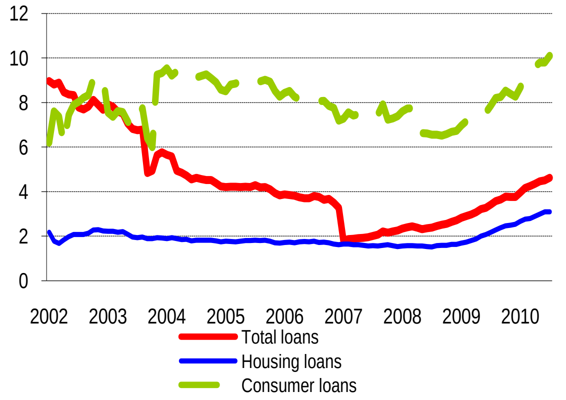


Source: CNB

9 Another factor supporting the probability of providing new client loans from banks' point of view was the establishment of the Czech Banking Credit Bureau. The basic purpose of the bureau is to allow banks and branches of foreign banks operating in the Czech Republic to share information about the payment prospects and credibility of their clients.

The non-performing loans ratio among households decreased until 2008, reflecting strong economic and labor market growth (see Figure 3.5). The default rate was lowest for housing loans and highest for consumer loans from banking institutions.[10] This was connected mainly with the fact that housing loans are usually provided to higher-income households, while consumer credit is drawn mostly by lower-income households. Since 2009 the escalating global financial and economic crises has worsened the ability of households to repay debt. The recent global financial crises has highlighted the importance of understanding how households respond to various macroeconomic shocks, and whether and how this reaction depends on their income, demographics, and level of indebtedness.

Figure 3.5: Non-performing loans (share in total loans in segments, %)



Source: CNB

3.2. Household-Level Data

In order to document the credit market trends at the household level, we use data from the Czech Household Budget Survey (HBS), an annual cross-sectional survey conducted by the Czech Statistical Office (CZSO), over the period 2000–2008. It contains information about household budget items and a range of socio-economic information about the household and its members, but most importantly it includes several questions about household credit. First, we know whether a household has a loan and, if it does, what type. Second, while we do not observe any amounts of loans outstanding, we know the total amount of loan repayments a household made in a given year, broken down by three types of loans (see below). Third, we know the amount of new loans taken out by a household in a given year, again broken down by three types of loans.

A household can have any of the following three types of loans: *housing loans*, *consumer loans*, and *other loans*. These loans are representative of three separate credit markets: 1) the housing credit market, represented by mortgages (with 50%–100% LTV) and construction

10 Note that consumer loans from banking institutions correspond to what we call other loans in the microdata analysis. Figures for the non-performing ratio of consumer loans from non-banking institutions (hereinafter called consumer loans) are not available for the whole economy.

saving loans (with 40%–100% LTV); note that construction loans are much more frequent among households than mortgages, and about one-tenth smaller in size; 2) the consumer credit market, represented by installment loans from non-banking institutions for purchases of durable goods; 3) the credit market for other types of loans, represented by overdrafts, credit cards, and unsecured consumer loans from banks.

Table 3.6: Size of the selected samples from Household Budget Surveys

YEAR	2000	2001	2002	2003	2004	2005	2006	2007	2008	ALL
Sample	2,994	3,045	3,038	2,760	2,883	2,877	2,752	2,765	2,685	25,799

Based on this information, we are able to construct the following variables for any type of loan or for one of the three types:

- whether the household has at least one loan
- whether the household was granted at least one new loan in a given year.
- the total amount of new loans granted in a given year.
- the total amount of loan repayments in a given year.

A household is defined as having a loan if it has either any loan repayments or any new loans granted in a given year. Having a new loan is defined based on a positive amount of new loans granted. Having an old loan is based on a positive amount of loan repayments. As the observed repayments in a given year may already be going toward a new loan taken out that year, our definition of having an old loan may overstate the share of households that have a loan from the previous year.

Households can report to the CZSO over a time period of 1–12 months. For the purposes of our research, we used only households which report a whole 12-month financial history in order to give all households the same chance to get a new loan and evaluate their yearly repayments.

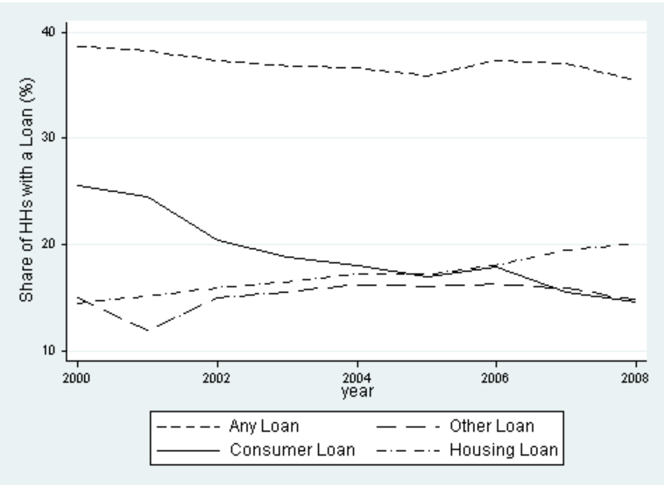
The data sample for each year represents 0.01% of all households in the population. All the descriptive tables and figures use sampling weights to ensure representativeness. The survey interviews are remunerated and the non-response is minimal in this data, so no information is imputed by the data provider. The original data is augmented with a supplementary sample of very-low-income households in order to ensure sufficient frequency of such households in the data. In our analysis, we omit this special focus group of observations, identified as households with zero sampling weights, from our analysis. The final sample size of our data set is given in Table 3.6.

3.3. Trends in Borrowing

The share of households with a loan was highest in 2000, when almost 39% of households had some type of loan (see Figure 3.7). Afterwards, this number steadily decreased, eventually reaching 36% in 2005. We can observe an increase between 2006 and 2007, when the economy was growing. The sharp decrease to 33% in 2008 was due to the financial crisis, when a deterioration of the labor market reduced households' demand for credit and mistrust among banks negatively affected supply. While the share of households with a loan was relatively stable over the period, the composition by types of loan changed substantially.

The housing loan market was growing over the entire period starting in 2000. While in 2000 only 14% of households had a housing loan, in 2008 the figure was 21%. The share of households with a housing loan increased even in 2008, the year of the crisis, when the other two markets dropped. In contrast to the housing loans market, the consumer loans market shrank significantly over the studied period. At the beginning of 2000, around 25% of households had a consumer loan. The figure had decreased by 10 percentage points by 2008. However, the amount of consumer loans granted rose, suggesting that loan accumulation occurred in the consumer loan market. The market for other loans grew between 2002 and 2004, but then remained stable until 2007, when a sharp decrease followed. On average, 16% of households had another loan type over the studied period. When we sum the numbers at the end of 2008, we can see that they add up to 50%. This is because one household can have multiple loans. From this we can conclude that at least 15% of households have multiple loans.

Figure 3.7: Share of households with a loan over time



Note: Weighted by sampling weights. Shares are in %.

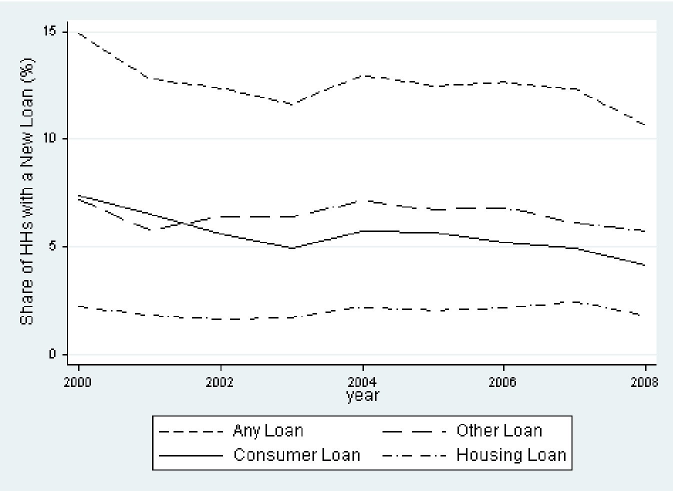
It is interesting to investigate the crowding-out among the three types of loans also from the perspective of the composition of loans by type. In 2000, among households that borrowed, 35% had another loan, 38% had a housing loan, and 66% had a consumer loan.[11] Corresponding to the borrowing patterns in Figure 3.7, there was a substantial increase in the share of housing loans to 63% and a significant decrease in consumer loans to 35% in 2008, i.e., the same as the proportion of households with other loans.

We now investigate the evolution of the share of households that take out a new loan, both overall and separately by type of loan (see Figure 3.8). The share of households with new loans dropped in 2003 but increased again to 13%. It remained fairly stable until 2007, but

11 As a single household can have multiple loans, the shares do not sum to 1.

decreased to 11% in 2008 in response to the beginning of the financial crisis. The housing loan market expanded as from 2004, peaking in 2007, when 2.4% of households took out a new housing loan. In 2008, the growth slowed, as the share of households with a new housing loan dropped by almost one-fifth compared to 2007. The consumer loans market was shrinking from 2000 until 2004, when there was sudden growth and almost 6% of households took out a new consumer loan. From then on, the market decreased again, down to 4% in 2008. The biggest growth in the market for other loans occurred in 2004, when 13% of households took out a new loan. The growth continued until 2006 and was followed by a decrease in 2007 and 2008, when only about 6% of households took out a new consumer loan.

Figure 3.8: Share of households with a new loan



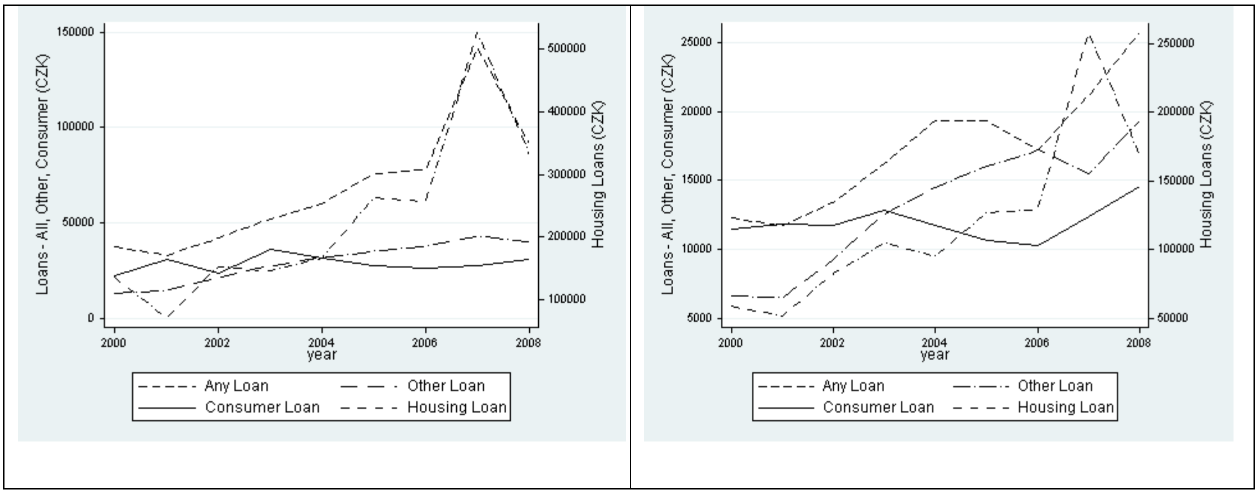
Note: Weighted by sampling weights. Shares are in %.

There are several plausible explanations for the growth in all types of loans in 2004. The first is increasing competition among lending institutions, which introduced more attractive products and more aggressive campaigns. The second factor is that information-sharing through external registers started to function fully in mid-2003. This may have contributed to better risk management and higher loan profitability, thereby creating room for expansion. The third factor is increasing demand for credit fostered by a rise in disposable income in 2004.

Further, we explore the evolution of the size of the total new loans granted (see Figure 3.9). Over time, the household credit market has grown substantially in volume. In 2002, the average newly granted loan was around CZK 40,000. As information-sharing and credit-scoring came into use in 2003, leading to better risk management and lower default risk, banks were willing to offer more loans with higher limits. At the same time, strong economic growth increased the demand for loans of bigger size. The average amount of new loans had doubled by 2005. This was followed by a further increase in 2007, fostered mainly by housing market growth. The average size of total new housing loans taken out by individual households was almost CZK 300,000 in 2005, and grew substantially to CZK 500,000 in

2007.[12] The expansion of both the housing market and the mortgage market accelerated in 2007, when an effective increase in taxes on construction work with effect from the beginning of 2008 was announced, resulting in an additional rise in the demand for housing. The credit market responded with an increase in the supply of mortgages, in terms of easier access and higher amounts. The average amount of total new consumer loans granted to households peaked in 2003, when it reached CZK 35,000. It then dropped for four years and rose again to CZK 30,000 in 2008. While the data suggest that loan accumulation takes place mostly through this market, the total amount of consumer loans obtained by households annually is rather small. The average amount of all new loans households are granted in the credit market for other loans has been constantly on the increase since 2000, reaching an average amount of CZK 40,000 in 2007. The maximum repayment period for unsecured consumer loans from banks (which are included among other loans in our classification) was extended from 5 to 7 years, an unusually long period compared to retail credit markets in other countries. The prolongation of the repayment period may have led to higher granted amounts, although it probably also increased the credit risk of the loans. While the median of the size of total newly granted loans, depicted in the right-hand panel of Figure 3.9, evolved in a very similar way to the average, there is a difference in 2008, when only the median of housing loans declined, while the median of the other two types of loans, as well as the median when all loans are considered, actually increased further.

Figure 3.9: Average (left-hand panel) and median (right-hand panel) size of newly granted loans



Note: Weighted by sampling weights. The housing loan scale is on the y-axis on the right.

The average number of loans a household has is another important feature of indebtedness. While, unfortunately, we do not have this information in our data, observing whether a household has loans of different types enables us to explore the number of types of loans (but not the number of loans of the same type). Over time, the average number of different loan types in our data set increased, reaching an average of 1.41 for the three loan types among

12 The relatively low amount for a housing loan is driven by the fact that construction loans (of much smaller size) are included among housing loans and are typically much more widely used than mortgages.

households with a loan in 2008. As for the composition, 65% of households had no loan, 23% had one type of loan, 10% had two types, and 2% had three types in 2008. Focusing only on households that borrow, 66% had one type of loan, 28% had two loan types, and 6% had three loan types in 2008.

3.4. Trends in Credit Accumulation

We next analyze to what extent households accumulate debt. Using micro data allows us to ask whether the stable annual share of households that borrowed over the analyzed period consisted always of new households that took out a new loan, or rather of the same households that re-borrowed. While we do not have panel data to address this question fully, we use the information about old loans and new loans to explore the degree of loan accumulation. Table 3.10 shows the share of households with a new loan among households that have an old loan, and looking backward, from the opposite perspective, the share of households with a new loan who also have an old loan. Among the households that had an old loan, 17.8% took out a new loan in 2008. Thus, almost one-fifth of households with an existing loan accumulated debt by taking out another loan. Looking at debt accumulation from the perspective of new loan borrowers, among households that took out a new loan in 2008, 50.6% had an old loan. Therefore, half of the growth in the credit market was driven by households that had an existing loan.

Table 3.10: Loan accumulation patterns

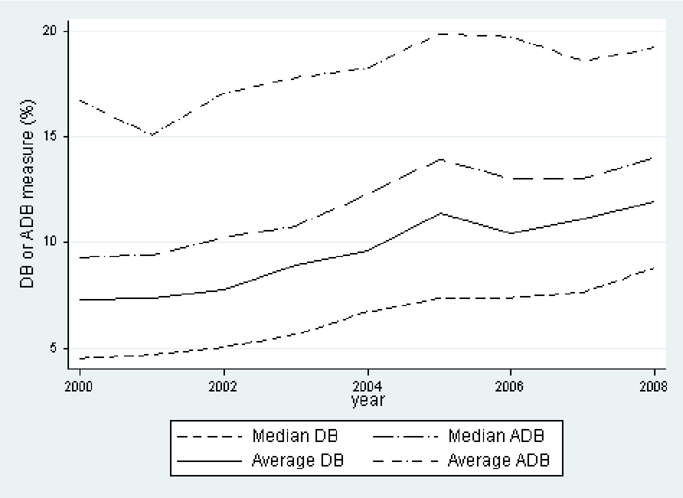
	OLD LOAN=1	NEW LOAN=1
Year	new_loan	old_loan
2000	21.24%	43.09%
2001	15.39%	36.18%
2002	17.57%	43.02%
2003	17.48%	45.85%
2004	19.71%	44.83%
2005	18.73%	43.21%
2006	18.62%	44.72%
2007	18.89%	46.81%
2008	17.77%	50.55%

Note: Weighted by sampling weights.

3.5. Debt Burden and Adjusted Debt Burden

Figure 3.11 documents the evolution of the two debt burden measures, the DB and the ADB, as defined in section 2. Overall, the debt burden rose over the analyzed period. The median debt burden almost doubled, starting at 4.5% in 2000 and ending at 8.8% in 2008. The median ADB increased from 9.3% to 14% over the analyzed period. The average DB and ADB grew from 7.3% to 12% and from 16.7% to 19.2%, respectively. We can also see that the debt burden increased sharply in 2005, the year of the household credit market boom, followed by a slight decrease in 2006. Subsequently, the debt burden grew again, albeit at a slower pace. The rise in the debt burden measures suggests that total loan repayments have increased relative to income, which has also grown since 2000, even in real terms. We expect both the rise in the amount of new loans and loan accumulation, as documented in previous subsections, to have contributed to the growth in households' annual loan repayments.

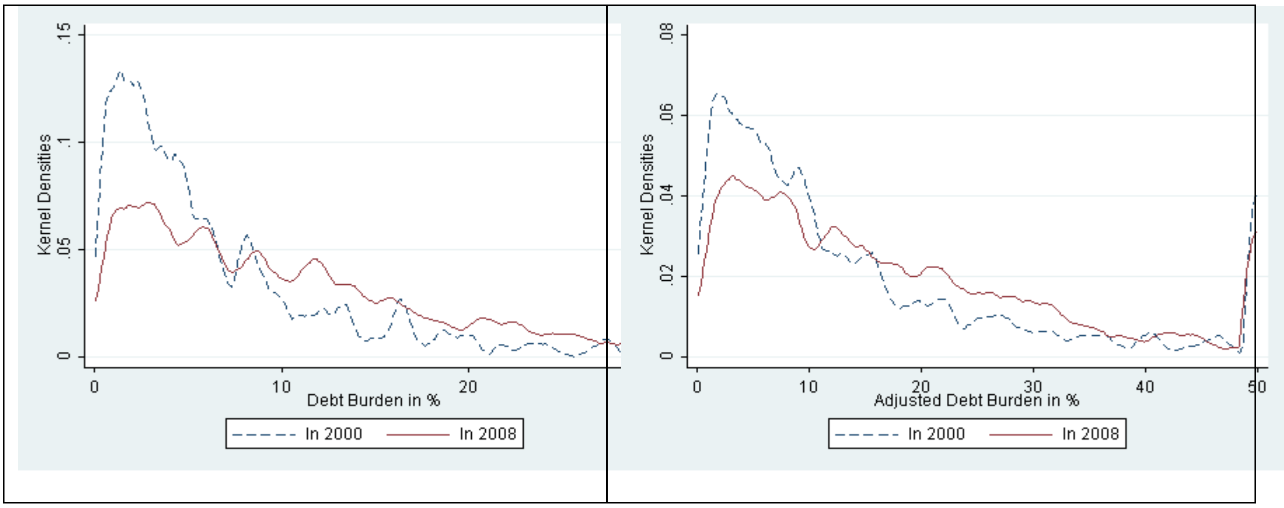
Figure 3.11: Evolution of the average and median DB and ADB over time



Note: Weighted by sampling weights

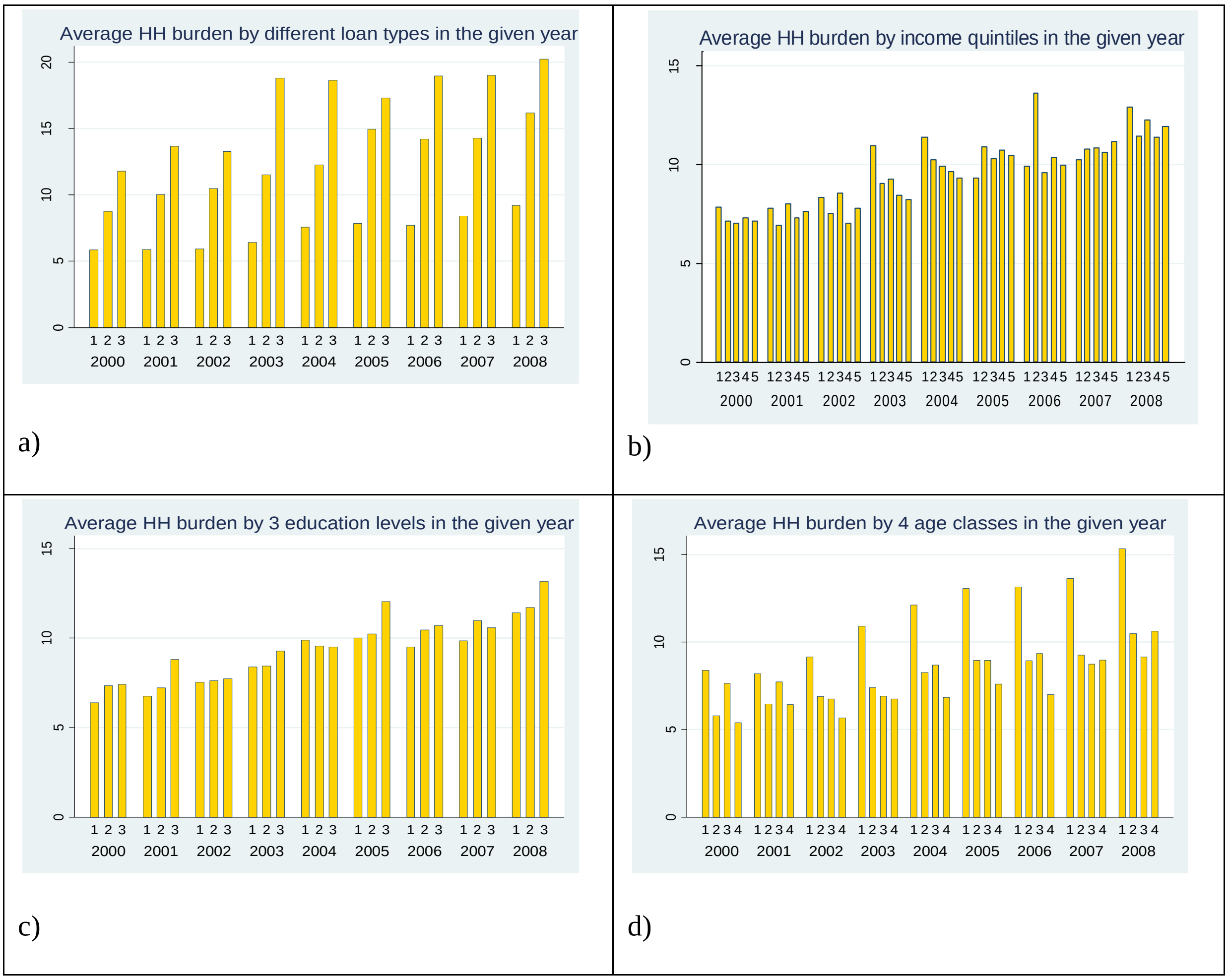
We next explore the distribution of the debt burden measures in the population of households that borrow. Figure 3.12 shows the distribution of the DB and the ADB among households that borrow, comparing the years 2000 and 2008. For both measures, the distribution gradually moved towards higher levels over the analyzed period, but for the DB the change was greater. While a majority of households were concentrated below the 10% level in 2000, almost half of the population had moved above this level by 2008.

Figure 3.12: Changes in the distribution of the debt burden and adjusted debt burden



Note: Kernel densities of the debt burden in 2000 and 2008. Source: Household Budget Surveys. The frequency weights used are based on sampling weights to simulate the whole population of households that borrow. The DB is censored at the value of 30, and the ADB is censored at the value of 50. Kernel densities are based on the Epanechnikov weighting function and the "optimal" bandwidth that would minimize the mean integrated squared error if the data were Gaussian and a Gaussian kernel was used (STATA default option).

Figure 3.13: Average debt burden across household characteristics



Note: Weighted by sampling weights.

We next disaggregate the average debt burden of households by number of loans, income, education, and age. It is rather obvious that the debt burden is an increasing function of the number of types of loans a household has. The burden of households with one loan type was around 5% in 2000 and rose further to 8% in 2008 (see Figure 3.13a). The debt burden of households with two types of loans was 8% in 2000 and increased to twice as much in 2008. Households with all three loan types had an average debt burden of 13% in 2000, which also gradually increased, reaching 20% in 2008.

The distribution of the debt burden across the five income quintiles shows that until 2006 it was the lowest income group that had the highest debt burden among all income groups (see Figure 3.13b). However, starting from 2005, the debt burden increased mainly among households in the highest income group. However, there was an overall increase in the average debt burden across all income groups as credit gradually became accessible to all of them.

Furthermore, we look at the distribution of the debt burden across three levels of education: 1 – basic education, 2 – high school education, and 3 – university education. The debt burden is an increasing function of education level (see Figure 3.13c). While the lowest education group had an average debt burden of 6% in 2002, the figure had risen to 11% by 2008. Households with a medium education level had an average debt burden equal to 7% in 2000, increasing to 11.5% in 2008. The debt burden of high-education households in 2000 was at the same level as the average debt burden of the medium education group, namely 7%, but it subsequently rose, reaching 13% in 2008. Although the differences in the debt burden across education levels are small, it is still clear that the highest average debt burden is concentrated in the segment of the most educated households.

We also document the differences in debt burden across four age groups: 1 – households younger than 38, 2 – households younger than 51, 3 – households younger than 60, and 4 – households older than 59. The highest debt burden is concentrated among the youngest population (see Figure 3.13d), with an average debt burden of just over 15%. The debt burden in the remaining three age groups evolved in a similar manner, reaching 12% in 2008. The distribution of the ADB across the four different household characteristics (not presented) is fairly similar to that of the DB.

4. Who Borrows?

We next use HBS data to analyze the key determinants of the observed household borrowing patterns described in the previous section. In particular, we estimate probit models of the probability that a household has a loan and that a household takes out a new loan in a given year, and tobit models of the size of the total new loans taken out in a given year and of a household's debt burden. All models are estimated on pooled annual data over the period 2000–2008 with year and regional effects included.

4.1. Model Specification

We considered all information available in our data for the estimation and, based on both their economic and statistical importance, eventually selected a subset of variables, which are listed and defined in Table 4.1. The choice and meaning of most of the variables are straightforward, but two of them deserve further discussion. We use and interpret the variable *Games-Lottery* (whether a household has expenditures on games and lottery) as a proxy for risk-loving, and the variable *Private pension plan* (whether a household saves for retirement via a private pension plan[13] to complement the public pension) as a proxy for financial literacy.[14]

In our models of the probability of taking out a new loan and of the size of the new loan granted, we also include a variable containing information on whether a household has an existing loan in order to explore loan accumulation. We then ask how and whether the extent of loan accumulation changed once information-sharing existed in the market. We construct a variable CBCB, which indicates the presence of a credit bureau in the market, as follows: CB equals 0 for the years 2000–2003 and equals 1 for the remaining periods, starting with 2004.[15] We include this variable interacted with the information on whether a household has an existing loan in order to explore the effect of information-sharing on the rate of loan accumulation.[16]

Table 4.1: List of variables used in the estimation

Variable name	Variable description
Year: 2000-2008	Year dummy variables; base category is year 2000
Region1-Region14	Region effects based on region where household resides (not presented)
Town, Village	Degree of urbanization: town, village, or city (base category)
Incquint1-Incquint5	Indicators of quintile in which household's income belongs. Quintiles are calculated for each year separately. Base category is lowest quintile, Incquint1.
Has other income	Dummy variable that household had unexpected or rare income in given year
Age	Age of head of household in years; base less than 37
High School, University	Highest education level achieved in household: basic education (base category), high school, and university
Mrg	Duration of marriage (in years), base category is less than 17 years or not married
Has child	Dummy that there is dependent child in household
Alone	Dummy that there is just one person in household
Member	Number of members of household
Employer, Pubemployee, Selfemployed, Retired, Housewife, Nojob_other	Type of employment: employer, self-employed, employee in public sector, retired, housewife, no job, employee in private firm (base category)
Home owner	Dummy that household lives in its own property
Games-Lottery	Dummy that household spends money on hazard games and lottery
Pension Private Plan	Dummy that household saves in private pension plan
Old loan	Dummy that household has existing loan when it receives new one (in regressions for new loan occurrence and new loan size)

[13] This is basically a non-mandatory private defined-contribution retirement saving scheme.

[14] While expenditure on games and saving in a private pension plan may also signal households' financial reserves and lower risk exposure, we still regard these two rather distinct items as reasonably good proxies for attitude to risk and financial management ability, respectively.

15 Following the establishment of the Czech Banking Credit Bureau (CBCB) in 2000, information-sharing came into use by five major banks operating in the Czech credit market in the middle of 2003. We expect that it took banks at least 6 months to adjust their strategies and evaluation of loan applications to include additional information from the credit bureau.

16 Note that we cannot include this variable in our models of the probability of having a new loan and of the size of new loans together with year effects due to perfect multicollinearity.

CBCB	Binary indicator of whether credit bureau exists in given year (starting 2004).
ConsLoan	Dummy that household has consumer loan
HouseLoan	Dummy that household has housing loan
OthLoan	Dummy that household has other loan

4.2. Determinants of Borrowing

The average marginal effects from the probit model of the probability that the household has at least one loan, regardless of the type of loan, are reported in Table 4.2. Consistent with the descriptive statistics from the previous section, which showed that the share of households remained stable, the time trend does not influence the probability that a household borrows in the credit market. The probability of having a loan increases with income, the size of the household, and the presence of children, but decreases with age and the duration of marriage. Household income and age are the biggest determinants of borrowing in terms of magnitude. Households with more educated members are less likely to borrow. Households with members who are employers or self-employed are less likely to be granted a loan, while employees in the public sector are more likely to be granted a loan, as compared to the basic (omitted) category, namely, employees in the private sector. We conjecture that this is mostly driven by restrictions on the supply side, as employers and the self-employed represent higher risk and uncertainty (due to greater income volatility and inability to prove true income), whereas the stability of public employees' jobs serves as a signal reducing the risk of default when compared to private employees, making credit-granting institutions reluctant to grant loans to the former and more prone to grant loans to the latter. In line with our expectations, both risk aversion and financial literacy increase the probability that the household has a loan.

Table 4.2: Probability of having a loan

Variable	AME	St.err.	Variable	AME	St.err.
2001	0.00269	(0.0350)	High school	-0.0773***	(0.0213)
2002	-0.0177	(0.0351)	University	-0.0982***	(0.0307)
2003	-0.00953	(0.0359)	mrg>17 & mrg<=25	-0.177***	(0.0311)
2004	-0.00722	(0.0356)	mrg>25 & mrg<=35	-0.296***	(0.0340)
2005	-0.00218	(0.0358)	mrg>35	-0.437***	(0.0444)
2006	0.0514	(0.0362)	Haschild	0.0737**	(0.0335)
2007	0.0517	(0.0363)	Alone	-0.195***	(0.0392)
2008	0.0260	(0.0368)	Member	0.0520***	(0.0155)
Village	0.0106	(0.0283)	Employer	-0.302***	(0.0570)
Town	0.0228	(0.0265)	Pubemployee	0.0881***	(0.0203)
Incquint2	0.163***	(0.0414)	Selfemployed	-0.202***	(0.0252)
Incquint3	0.345***	(0.0460)	Retired	0.0186	(0.0373)
Incquint4	0.495***	(0.0492)	Housewife	-0.0331	(0.0324)
Incquint5	0.569***	(0.0535)	Nojob_other	-0.0998**	(0.0470)
Hasotherinc	0.162***	(0.0184)	Homeowner	0.0529***	(0.0195)
age>37 & age<=50	-0.262***	(0.0251)	Games-Lottery	0.109***	(0.0182)
age>50 & age<=59	-0.451***	(0.0313)	Private pension plan	0.155***	(0.0184)
age>59	-0.747***	(0.0449)	Constant	-0.700***	(0.0691)

Note: Average marginal effects (AME) and standard errors from the probit model of the probability of having a loan. Pooled data for 2000–2008. Regional dummies are included; Prague is the base category. Pseudo R2 is 0.14. The base category is represented by households with private employees, income in the lowest quintile, basic education, age below 37, and duration of marriage below 17 years, who reside in a city, in the year 2000. *** p<0.01, ** p<0.05, * p<0.1

The results from our second regression, a probit model of the probability that a household takes out a new loan in a given year, given in Table 4.3, are fairly close to the previous model, suggesting that the probabilities of having a loan and of taking out a new one are determined by similar factors in a similar way.

The only difference is the opposite sign of home ownership in the two models. As will be discussed later, this is due to the fact that home owners finance the purchase of their home via mortgages, which increases their probability of having a loan, but, as they already have a loan to repay, they are less likely to take out another loan.

There are, however, two additional variables in the model of the probability of taking out a new loan, as compared to the model of the occurrence of an existing loan: information on whether a household has an existing loan, and its interaction with the indicator for the existence of information-sharing.

Table 4.3: Probability of taking out a new loan (with an old loan and information-sharing)

Variable	AME	St.err.	Variable	AME	St.err.
2001	-0.0933**	(0.0419)	age>59	-0.512***	(0.0590)
2002	-0.122***	(0.0422)	high school	-0.0364	(0.0262)
2003	-0.146***	(0.0435)	University	-0.113***	(0.0380)
2004	-0.110**	(0.0455)	mrg>17 & mrg<=25	-0.0697*	(0.0377)
2005	-0.138***	(0.0458)	mrg>25 & mrg<=35	-0.205***	(0.0441)
2006	-0.105**	(0.0463)	mrg>35	-0.298***	(0.0600)
2007	-0.112**	(0.0465)	Haschild	0.00217	(0.0404)
2008	-0.206***	(0.0481)	Alone	-0.128***	(0.0491)
Village	-0.126***	(0.0335)	Member	0.0628***	(0.0180)
Town	-0.136***	(0.0311)	Employer	-0.419***	(0.0817)
incquint2	0.0170	(0.0530)	Pubemployee	-0.00751	(0.0245)
incquint3	0.0635	(0.0584)	Selfemployed	-0.244***	(0.0326)
incquint4	0.111*	(0.0620)	Retired	0.0710	(0.0486)
incquint5	0.148**	(0.0667)	Housewife	0.0255	(0.0370)
Hasotherinc	0.264***	(0.0223)	nojob_other	-0.0521	(0.0564)
Oldloan	0.0394	(0.0321)	Homeowner	-0.0858***	(0.0233)
Oldloan*CBCB	0.120***	(0.0424)	Games-Lottery	0.120***	(0.0219)
age>37 & age<=50	-0.203***	(0.0295)	Private Pension Plan	0.0942***	(0.0226)
age>50 & age<=59	-0.278***	(0.0388)	Constant	-1.291***	(0.0856)

Note: Average marginal effects (AME) and standard errors from the probit model of the probability of taking out a new loan in a given year. Pooled data for 2000–2008. Regional dummies are included; Prague is the base category. Pseudo R2 is 0.09. The base category is represented by households with private employees, income in the lowest quintile, basic education, age below 37, and duration of marriage below 17 years, who reside in a city, in the year 2000. CBCB captures the existence and use of the credit bureau and is defined as zero for 2000–2003 and one for 2004–2008. *** p<0.01, ** p<0.05, * p<0.1

While the average marginal effect of having an existing loan on the probability of taking out a new loan is positive but insignificant, it is 0.12 and significant at 1% when interacted with the indicator of the presence of the credit bureau. This means that having an existing loan increases the probability of taking out a new loan by 12 p.p., but only when there is information-sharing in the market. We conclude that the observed loan accumulation was mostly driven by credit-granting institutions: as access to information about households' credit histories reduced the uncertainty about their repayment ability and behavior, credit-granting institutions were more likely to grant new loans to these households.

Table 4.4: Model of the size of total new loans

Variable	AME	St.err.	Variable	AME	St.err.
2001	-0.212*	(0.108)	high school	-0.0682	(0.0675)
2002	-0.256**	(0.109)	University	-0.181*	(0.0966)
2003	-0.270**	(0.112)	mrg>17 & mrg<=25	-0.181*	(0.0960)
2004	-0.0415	(0.109)	mrg>25 & mrg<=35	-0.535***	(0.113)
2005	-0.0446	(0.110)	mrg>35	-0.721***	(0.156)
2006	0.0827	(0.110)	Haschild	0.0708	(0.103)
2007	0.261**	(0.110)	Alone	-0.291**	(0.126)
2008	-0.107	(0.114)	Member	0.0899**	(0.0456)
Village	-0.292***	(0.0850)	Employer	-0.899***	(0.207)
Town	-0.329***	(0.0791)	Pubemployee	-0.0208	(0.0621)
incquint2	0.134	(0.138)	Selfemployed	-0.597***	(0.0833)
incquint3	0.311**	(0.151)	Retired	0.127	(0.126)
incquint4	0.526***	(0.159)	Housewife	0.105	(0.0929)
incquint5	0.777***	(0.171)	nojob_other	-0.216	(0.145)
Hasotherinc	0.561***	(0.0572)	Homeowner	-0.158***	(0.0593)
age>37 & age<=50	-0.611***	(0.0749)	Games-Lottery	0.299***	(0.0558)
age>50 & age<=59	-0.822***	(0.0992)	Private pension plan	0.211***	(0.0576)
age>59	-1.346***	(0.153)	Constant	-3.647***	(0.224)

Note: Average marginal effects (AME) and standard errors for the intensive margin (among households that borrow) from the tobit model of the total amount of new loans taken out in a given year. Pooled data for 2000–2008. Regional dummies are included; Prague is the base category. Pseudo R2 is 0.06. The base category is represented by households with private employees, income in the lowest quintile, basic education, age below 37, and duration of marriage below 17 years, who reside in a city, in the year 2000. Loan size is in CZK 100,000.
*** p<0.01, ** p<0.05, * p<0.1

Third, we estimate a tobit model of the amount of all new loans taken out in a given year. Table 4.4 presents the results in terms of the average marginal effects for the intensive margin, i.e., the effects of the variables on the size of total new loans taken out in a given year, conditional on at least one new loan being taken out in a given year. The results are in line with our findings for the probabilities of having a loan and of having a new loan in a given year. This suggests that the frequency (in terms of households with a loan) and intensity (in terms of the loan sizes) are determined by similar factors. We can see that households in towns and villages have smaller amounts of total new loans granted in a given year compared to households in cities. This is most probably driven by rural versus urban differences in housing and other prices as well as differences in household income. Younger households have higher amounts of total new loans. We conjecture that this result is mostly demand driven, as such households have current housing needs for starting families and also have the longest consumption-smoothing horizon. Employers and self-employed households not only have a smaller probability of having a loan and of being granted a new one, but also take out and are granted smaller loan amounts than employees. We again conjecture that this is driven by a limited supply of credit, as banks use tax returns when granting loans and entrepreneurs typically optimize their income across years in order to pay lower taxes, which may undervalue their true ability to repay in banks' eyes. Finally, as expected, households with lower risk aversion and higher financial literacy tend to borrow greater amounts.

Like the positive effect of having an existing loan on the probability of taking out a new one, the fact that a household already has a loan increases the amount of new loans, but again only once the credit bureau is in effect. Starting in 2004, having an existing loan increases the amount of new loans taken out, conditional on a new loan being taken out, by CZK 24,700, but it has no effect prior to that year.

Table 4.4: Model of the size of total new loans (with an old loan and information-sharing)

Variable	AME	St.err.	Variable	AME	St.err.
2001	-0.212*	(0.108)	age>59	-1.314***	(0.153)
2002	-0.256**	(0.109)	high school	-0.0628	(0.0676)
2003	-0.270**	(0.112)	University	-0.178*	(0.0967)
2004	-0.140	(0.117)	mrg>17 & mrg<=25	-0.176*	(0.0962)
2005	-0.141	(0.118)	mrg>25 & mrg<=35	-0.521***	(0.114)
2006	-0.0197	(0.118)	mrg>35	-0.694***	(0.156)
2007	0.159	(0.118)	Haschild	0.0668	(0.103)
2008	-0.215*	(0.123)	Alone	-0.280**	(0.126)
Village	-0.300***	(0.0852)	Member	0.0919**	(0.0457)
Town	-0.335***	(0.0792)	Employer	-0.893***	(0.207)
incquint2	0.126	(0.138)	Pubemployee	-0.0249	(0.0622)
incquint3	0.291*	(0.151)	Selfemployed	-0.592***	(0.0835)
incquint4	0.497***	(0.160)	Retired	0.120	(0.126)
incquint5	0.742***	(0.172)	Housewife	0.104	(0.0930)
hasotherinc	0.558***	(0.0573)	nojob_other	-0.208	(0.145)
Oldloan	0.00991	(0.0827)	Homeowner	-0.169***	(0.0594)
oldloan*CBCB	0.247**	(0.108)	Games lottery	0.298***	(0.0559)
age>37 & age<=50	-0.600***	(0.0751)	pension insurance	0.201***	(0.0578)
age>50 & age<=59	-0.800***	(0.0996)	Constant	-3.625***	(0.225)

Note: Average marginal effects for the intensive margin (among households that borrow) from the tobit model of the total amount of new loans taken out in a given year. Pooled data for 2000–2008. Regional dummies are included. Pseudo R2 is 0.06. The base category is represented by households with private employees, income in the lowest quintile, basic education, age below 37, and duration of marriage below 17 years, who reside in a city, in 2000. CBCB captures the existence and use of the credit bureau and is defined as zero for 2000–2003 and one for 2004–2008. *** p<0.01, ** p<0.05, * p<0.1

Information-sharing allows credit-granting institutions to differentiate among households based on their past borrowing and repayment behavior and therefore grant households with good credit histories higher limits on the amounts of new loans compared to households with bad or no credit history. Given our results, shared information about an existing loan – at the early stage of development of the credit market and still relatively low levels of debt –

apparently served as a positive signal of clients' experience with borrowing. While in this sense the CBCB also contributed to loan accumulation, we expect that with further expansion of credit, it will also serve as an indicator of overindebtedness and prevent lending institutions from extending credit to households with too much credit relative to their repayment ability. We analyze the evolution of the debt burden and its distribution among households that borrow in the next section.

4.3. Determinants of the Debt Burden

The average marginal effects from the tobit model of the debt burden are presented in Table 4.5. In line with the descriptive section, the yearly fixed effects suggest that the debt burden has been increasing since 2004. The results suggest that in contrast to borrowing patterns, the debt burden does not significantly differ with the degree of urbanization. We interpret this as being a result of the fact that the levels of debt, income, and costs differ across urban locations in a similar way, so that the ratio of loan repayments to income stays the same. Similar to the estimation results for the patterns of borrowing, the debt burden is higher among high-income groups, the younger population, and couples with a lower duration of marriage. Single-member households have a lower debt burden. Employers and the self-employed have a lower debt burden than employees, and both risk-loving and financial literacy also foster more debt accumulation.

Table 4.5: Debt burden model

Variable	Beta	St.err.	Variable	Beta	St.err.
2001	0.0918	(0.592)	high school	-1.045***	(0.361)
2002	0.125	(0.593)	University	-0.591	(0.512)
2003	0.943	(0.605)	mrg>17 & mrg<=25	-2.839***	(0.514)
2004	1.675***	(0.598)	mrg>25 & mrg<=35	-4.819***	(0.586)
2005	2.394***	(0.600)	mrg>35	-6.739***	(0.794)
2006	2.677***	(0.606)	Haschild	0.00963	(0.557)
2007	3.093***	(0.608)	Alone	-3.560***	(0.670)
2008	3.195***	(0.616)	Member	0.0438	(0.252)
Village	0.315	(0.470)	Employer	-3.063***	(0.966)
Town	0.149	(0.440)	Pubemployee	0.675**	(0.335)
incquint2	2.568***	(0.733)	Selfemployed	-2.558***	(0.423)
incquint3	5.420***	(0.803)	Retired	-0.288	(0.650)
incquint4	7.578***	(0.852)	Housewife	1.321**	(0.516)
incquint5	9.105***	(0.919)	nojob_other	-1.246	(0.788)
Hasotherinc	1.856***	(0.307)	Homeowner	1.570***	(0.326)
age>37 & age<=50	-4.698***	(0.407)	Games lottery	1.737***	(0.303)
age>50 & age<=59	-7.619***	(0.530)	pension insurance	2.078***	(0.309)
age>59	-13.75***	(0.786)	Constant	-13.35***	(1.188)

Note: Average marginal effects for the intensive margin (among households that borrow) from the tobit model of households' debt burden, defined as the ratio of loan repayments to net income. Pooled data for 2000–2008. Regional dummies are included. Pseudo R2 is 0.04. The base category is represented by households with private employees, income in the lowest quintile, basic education, age below 37, and duration of marriage below 17 years, who reside in a city, in 2000. *** p<0.01, ** p<0.05, * p<0.1

Note that homeowners have a higher debt burden than non-homeowners, which again suggests that most of them used a mortgage to finance their home purchase.

We next analyze which type of loan contributed the most to the increase in the debt burden by augmenting the model in Table 4.5 with a series of interaction terms of year fixed effects and three indicators of the types of loans a household may have. In Table 4.6 we report just the average marginal effects of the interaction terms and their components. The effects of the remaining variables remain practically unchanged when compared with the results in Table 4.5.

In line with the observed stable share of households that borrow but the rapidly changing composition of the types of loans households obtain, year fixed effects are not significantly different from zero and the evolution of the debt burden overtime is mostly explained by changes in the use of the different types of loans. While consumer loans formed the largest part of the debt burden in 2000, followed by housing loans and other loans, this pattern reversed over the analyzed period. Expansion of housing loans (starting in 2005, but in particularly in 2007) was the main source of the increase of the debt burden, complemented by other loans, while the contribution of consumer loans decreased over time. The results for the model of the ADB (not presented here) are fairly close to the results for the DB.

Table 4.6: Debt burden model

Variable	Margins	St.err.	Variable	Margins	St.err.
2001	-0.440	(0.873)	Consloan	20.34***	(0.755)
2002	0.139	(0.860)	consloan*2001	0.579	(1.047)
2003	-0.507	(0.890)	consloan*2002	-0.743	(1.057)
2004	1.049	(0.859)	consloan*2003	-0.409	(1.087)
2005	1.337	(0.857)	consloan*2004	-1.619	(1.071)
2006	1.247	(0.871)	consloan*2005	-2.264**	(1.080)
2007	0.782	(0.885)	consloan*2006	-2.552**	(1.086)
2008	0.994	(0.886)	consloan*2007	-2.513**	(1.104)
Houseloan	19.03***	(0.824)	consloan*2008	-3.519***	(1.122)
houseloan*2001	0.872	(1.144)	Othloan	10.63***	(0.827)
houseloan*2002	1.211	(1.134)	othloan*2001	1.810	(1.206)
houseloan*2003	2.586**	(1.156)	othloan*2002	2.361**	(1.160)
houseloan*2004	0.581	(1.126)	othloan*2003	5.769***	(1.167)
houseloan*2005	3.918***	(1.128)	othloan*2004	6.193***	(1.149)
houseloan*2006	2.738**	(1.130)	othloan*2005	5.870***	(1.152)
houseloan*2007	5.454***	(1.129)	othloan*2006	6.542***	(1.154)
houseloan*2008	5.527***	(1.129)	othloan*2007	6.506***	(1.165)
			othloan*2008	7.109***	(1.181)

Note: Average marginal effects for the intensive margin (among households that borrow) from the tobit model of households' debt burden, defined as the ratio of loan repayments to net income. The specification of the tobit model is as in Table 4.7, but augmented with three types of loan and their interactions with year dummies (only the effects of these additional variables are reported in the table), in order to explore the contribution of each type of loan to debt accumulation. Pooled data for 2000–2008. Pseudo R2 is 0.14. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

5. Who May Not Repay?

5.1. SILC Data and Trends in Repayment Difficulties

Until now, we have explored our principal dataset (the HBS) in order to determine which households borrow, how much they borrow, and to what extent they accumulate loans relative to income, as the main indicator of their repayment ability. As the HBS does not contain any information about households' repayment behavior, financial difficulties or default, we have not been able to assess whether households borrow above their repayment limits, what level of indebtedness relative to income is likely to lead to default, and whether the observed borrowing patterns create threats to financial stability.

We will now use an additional dataset which contains information about households' repayment behavior in order to answer at least some of these questions. The additional data come from the "Statistics on Income and Living Conditions" (SILC), which is an annual survey collected again by the Czech Statistical Office, available for the period 2005–2008.[17] The aim of the survey was to gather representative data on income distribution and the quality and affordability of housing, but it also contains a series of other socio-economic characteristics, including information about households' delayed payments (of electricity, gas, and cell phone bills, of rent, and of mortgage and other loan repayments) and households' perception of their financial situation. Unfortunately, the dataset lacks some of the crucial economic variables that are present in the HBS, in particular the amount of annual repayments of loans and the amount of total new loans in a given year.

Table 5.1: Evolution of the default rate and borrowing patterns in the SILC dataset

Year	HH with a loan %*	Sample size (HH with a loan)	Delayedpay %*
2005	28.44%	1,159	10.89%
2006	29.24%	2,015	9.16%
2007	27.30%	2,454	5.90%
2008	27.93%	2,872	4.92%

Note: Source: SILC 2005–2008. Weighted by sampling weights.* Share of households that missed at least one loan repayment in the given year among all households that have a loan.

In order to analyze repayment behavior, we restrict our sample to households that have a loan, i.e., households that report that they are repaying a mortgage or another loan in a given year. The share of households with a loan, the size of the sample of households with a loan, and their repayment behavior are summarized in Table 5.1. Note that repayment behavior is captured by information about any delayed payments on a loan,[18] i.e., whether the household

17 Note that the few occurrences of non-response are dealt with by the CZSO by imputation methods based on standard statistical procedures.

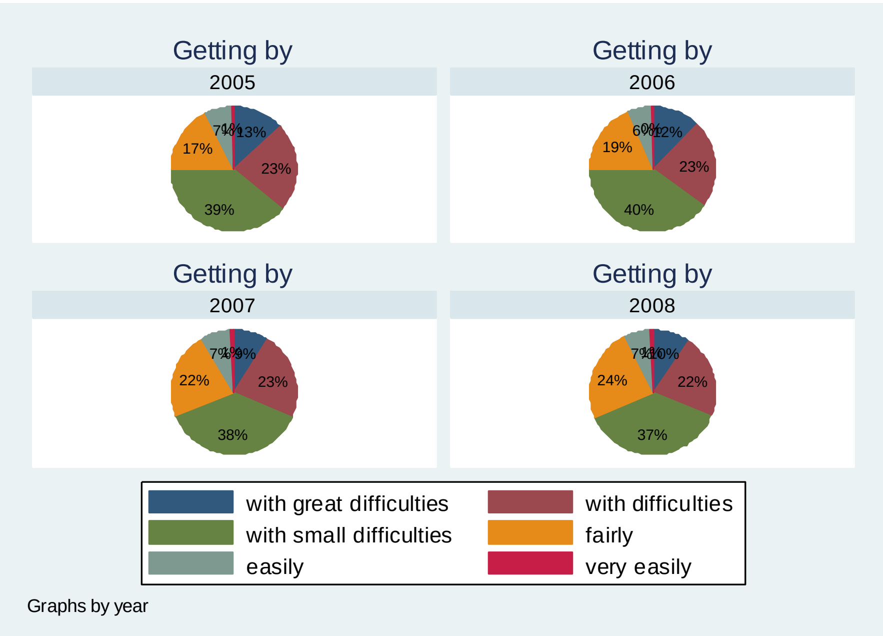
18 Unfortunately, the number of delayed payments and the length of delay are not reported in the data.

failed to repay at least one loan installment on time. It is this information which we use as a – rather broad – *definition of default* in this paper.

Households' perceptions of getting by are displayed in Figure 5.2. In line with the decreasing rate of delayed payments, households' subjective assessment of their financial situation, reported in Figure 5.2. suggests that their cash flow management improved over the analyzed time period.

The percentage of households with any delayed payments on their loans in the given year decreases substantially over time, starting at almost 11% in 2005 and reaching about 5% in 2008. We conjecture that the decrease in the share of households that miss their repayments is driven mostly by two factors: first, the relatively strong economic growth over the analyzed period, and second, a gradual improvement in lenders' credit-scoring techniques, which help avoid loans being granted to risky households.

Figure 5.2: Households' subjective assessment of their financial situation



Note: Source: SILC 2005–2008. Sample contains households with a loan. Weighted by sampling weights

5.2. Combining Repayment Behavior with Imputed Debt Burden Levels

We next try to relate the extent of households' indebtedness, as captured by the debt burden, to their repayment behavior. As already mentioned, while the HBS dataset, which we use to analyze households' debt burden ratios, lacks information on repayment behavior, the SILC dataset has both household income and repayment behavior indicators, as summarized in the previous subsection, but has no information about the amount of loan repayments a household has to make.

Table 5.3: Variables used in the prediction of the amount of loan repayments

Variable name	Variable description
paid_this_year	Amount of loans repaid this year
year	Year dummy; base 2000
region	Region dummy; base Prague
houseloan	Dummy that HH has a house loan
type of flat	Flat type categories; base rental
HH type	Household categories; base couple without children
soc subsidy	Dummy that HH gets social subsidies
room nbr	Number of rooms HH flat has
meters 2	Surface area of flat
income quint	Income quintile
age	Age of head of HH
educ	Education level of HH; base basic
marriage age	Length of marriage of HH
marriage age2	Length of marriage of HH squared
public employ	Member of HH works for public sector
Retired	Member of HH is pensioner
Housewife	Member of HH is housewife

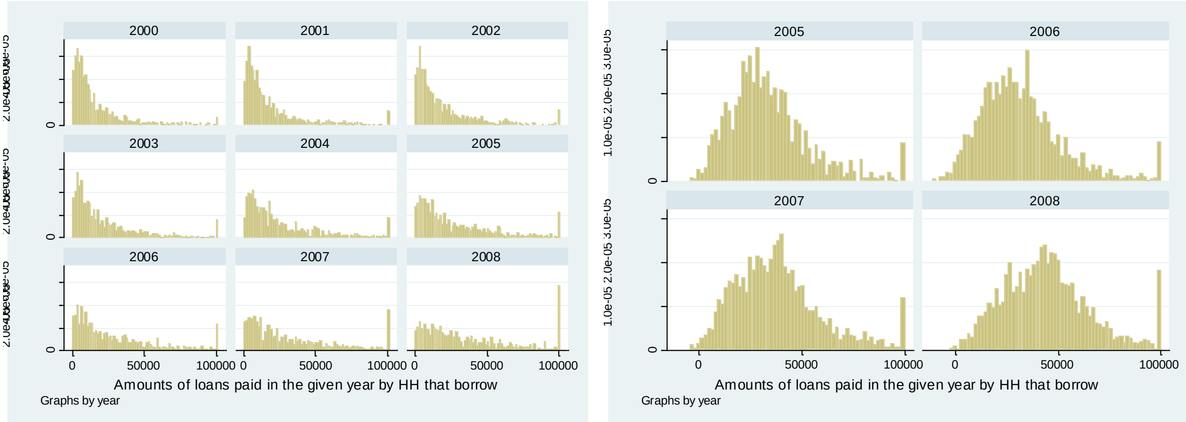
In order to explore the relationship between the debt burden and default, we need to combine the information from the two datasets. We choose to use the HBS dataset to predict the total annual loan repayments in the SILC data, where this information is missing. We first estimate a model of annual loan repayments using the HBS data and – based on our estimates – we then predict the annual loan repayments of households in the SILC dataset. For the purposes of this extrapolation, we use a linear regression model estimated only on households that have a loan in the given year.[19] As our goal is to achieve the best fit, we use all the variables which could have any predictive power for the amount of loan repayments in a given year and which are common to both datasets. The variables used for the extrapolation are listed in Table 5.3. The fit of the regression is $R^2 = 0.023$.[20]

In Figure 5.4, we compare the real values of the amount of loan repayments in the given year from the HBS (left) and the values of the annual amount of loan repayments predicted in the SILC dataset (right). We see that because our preferred estimation technique does not account for bottom truncation of loan repayments at zero, low values of loan repayments are overestimated in our predictions.

[19] This implies that we are using a truncated sample and our coefficients are most probably inconsistent. However, the tobit model on all households gave a much worse fit and we do not have any suitable exclusion restrictions for a two-equation model with censoring, which would be less restrictive than tobit.

[20] A scatter plot of the actual and within-sample-predicted amounts of loan repayments is presented in Table B.1 in the Appendix. The estimation results are available from the authors upon request.

Figure 5.4: Distribution of the amount of loan repayments – observed in the HBS and predicted in the SILC



HBS SILC predicted

Note: Weighted by sampling weights. Censored at CZK 100,000.

5.3. DB and ADB as Predictors of Default

Once we have the predicted annual amount of loan repayments of households in the SILC data, we calculate their DB and ADB and explore whether these measures correlate with their repayment behavior. In order to explore the relationship between our two debt burden measures and default, we divide households into 20 uniform groups with respect to their standard debt burden (SDB) and adjusted debt burden (ADB) and report the default rates across the 20 quantiles.[21] Figure 5.5 shows the overall relationship for the entire period 2005–2008, as well as for the individual years. Both the SDB and the ADB have relatively high discriminatory power toward the risk of default, as the default rates rise across the 20 quantiles for both definitions. However, the gradual increase in default rates across the 20 quantiles of the ADB measure is much more clear and “monotonic” than that of the SDB.

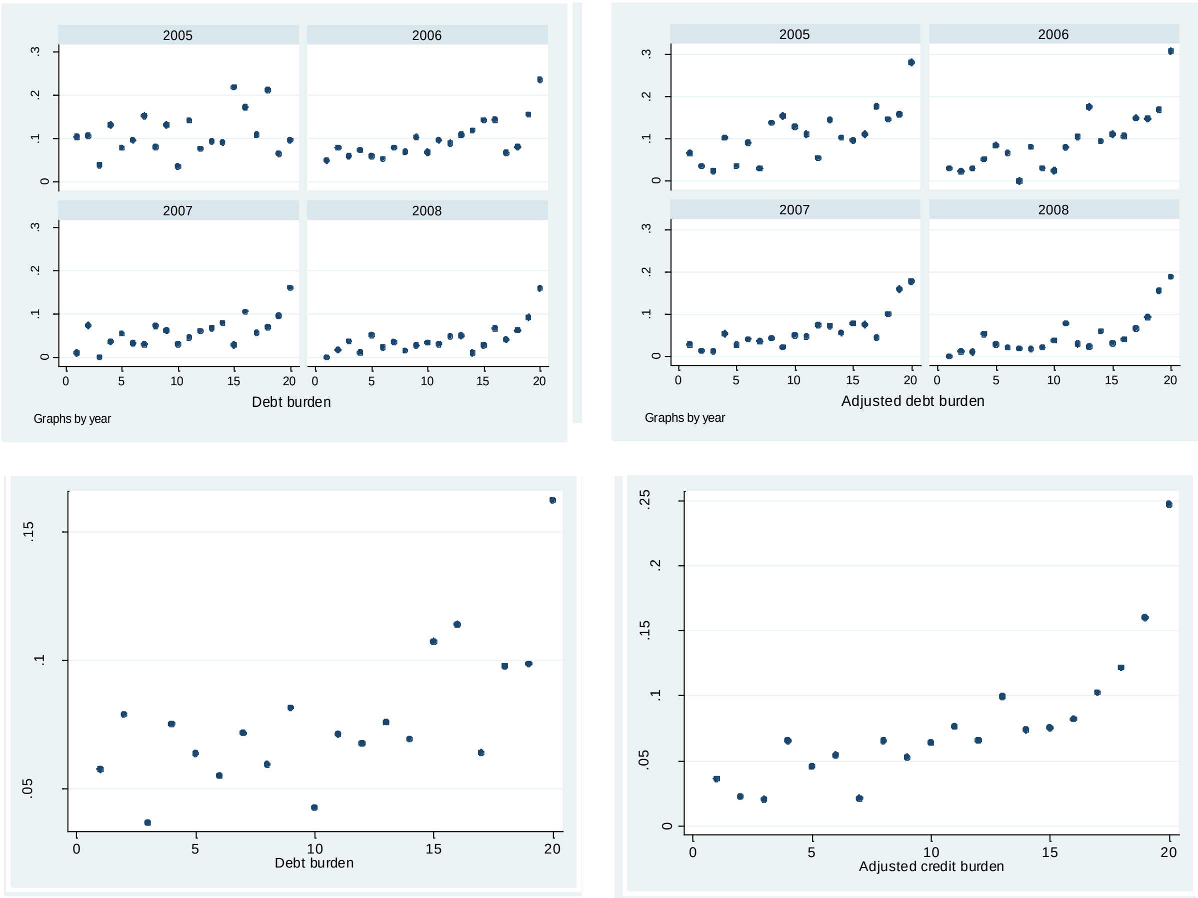
Based on the relationship between the SDB and ADB and default, we select the most important cut-off points of the two measures to differentiate across default rates, i.e., the points which can best separate the differences in default rates across these measures. Table 5.6 reports the default rates (i.e., the shares of households with delayed loan payments among households that have a loan) within the four groups defined by the most important cut-off points.

Inspecting the distribution of delayed payments across different SDB and ADB values, we find that the default rate substantially increases in the segment of households with an SDB

21 The absolute values of the cut-off points of the 20 quantiles of the SDB and ADB are listed in Table C.1 in the Appendix.

level greater than 15% and with an ADB level above 31%. In the first case the default rate reaches 10% in 2008. In the second it is almost 15% in 2008.

Figure 5.5: Comparison of the SDB and the ADB with respect to the default rate



Note: Weighted by sampling weights.

Table 5.6: Cut-off points for the SDB and the ADB

Debt Burden	2005	2006	2007	2008
<=7%	8.31%	6.29%	2.80%	1.79%
<=11%	10.59%	7.53%	4.52%	2.84%
<=15%	12.72%	11.15%	6.63%	4.08%
>15%	12.44%	15.79%	10.87%	10.45%

ADB	2005	2006	2007	2008
<=9%	4.14%	2.73%	1.79%	0.74%
<=19%	9.82%	5.19%	3.96%	3.42%
<=31%	11.38%	12.29%	6.62%	4.13%
>31%	19.40%	20.74%	14.52%	14.51%

Note: Default rates at different levels of the standard and adjusted debt burden measures.

We see that for both the SDB and the ADB, the average default rate decreases over time in all four groups, with the most substantial drop being in 2007. In the group with the highest debt burden, however, default declines at the slowest rate. The adjusted debt burden again seems to separate default better than the standard debt burden. Table 5.7 explores the relationship between the two measures and default formally, as it shows the household-level correlations between the SDB or the ADB and default. We see that the correlation between the ADB and default is more or less twice as high as the correlation between the SDB and default in all four years. We conclude that the adjusted debt burden separates default better than the standard debt burden definition.

Table 5.7: Correlations of the SDB and the ADB with default

	2005	2006	2007	2008
SDB	0.03	0.09**	0.13**	0.09**
ADB	0.12**	0.19**	0.17**	0.17**

Note: ** means significant at the 5% level

In addition, we propose to use an adjusted debt burden of above 30% as an indicator of households with too much debt relative to their repayment behavior. The corresponding default rate among overindebted households was 15% in 2008. We use this definition of *overindebtedness* in the remaining part of the paper. It should be emphasized, however, that this definition is overly cautious, as first, on average over the analyzed period only 17% of overindebted households did not make their loan repayments on time, and second, we expect that just a fraction of households with delayed payments eventually default.

The average values of the SDB and the ADB in the SILC data over the four years are reported in Table 5.9. Note that the values of the debt burden (especially the ADB) using the SILC data are higher than our results for the HBS. This is most probably a result of using predicted loan repayments based on our extrapolation techniques for the SILC measures. While the average debt burden slightly increased over the given period, the average adjusted debt burden fluctuated, with two peaks in 2005 and 2007 corresponding to the boom years in the household credit market. The table also shows that both monthly disposable income (net of taxes) and discretionary income (disposable income minus the living minimum) increased over the four years.

Table 5.9: Comparison of the SDB and the ABD over time

Year	Debt burden	Adjusted debt burden	Delayed pay	Disposable income	Discretionary income	Living min
2005	11.04%	31.69%	10.89%	26,438	16,632	9,852
2006	9.86%	24.20%	9.16%	27,076	17,163	9,962
2007	11.09%	27.37%	5.90%	29,233	19,074	10,199
2008	12.21%	23.02%	4.92%	32,327	21,962	10,401

Note: Weighted by sampling weights.

As discretionary income increased more (and relative to loan repayments) than disposable income between 2007 and 2008, we see that while the DB increased between the two years, the ADB actually fell. The corresponding default rate also decreased – a rather promising trend in financial stability terms, but one which changed sharply in 2009 as a consequence of the 2008 global financial crisis (see again the aggregate developments in section 3). The micro data for these years, however, are not available yet.

5.4. Loan-at-Risk Simulations

We now use our definition of overindebtedness (see the previous subsection) in combination with the limited information on loans that we have in the HBS – total annual installments on all outstanding loans and the total amount of new loans taken out in the given period – in order to infer what share of the corresponding totals in the population are at risk of default.[22] We calculate the corresponding population totals using frequency weights. Each household's amounts are multiplied by a number which captures how many households a particular household in our sample represents in the population.[23] Using our definition of overindebtedness, we identify households that are at risk of default as those whose adjusted debt burden exceeds 30%. We ask what share of total annual installments and what share of total new loans taken out in a given year belong to overindebted households. Furthermore, we use an average default rate of 17%[24] among overindebted households in order to determine the share of annual installments which are at risk of default. The results are shown in Table 5.4.1.

Table 5.4.1: At-risk shares of annual installments and new loans taken out

	Annual installments* (in millions of CZK or %)				New loans taken out (in millions of CZK)			
Year	Total	HHs with ADB>30	% by HH with ADB>30	At risk of default	Total	HHs with ADB>30	% by HH with ADB>30	At risk of default
2000	24,600	9,690	39.3%	6.69%	24,200	5,160	21.3%	3.62%
2001	27,100	10,600	38.9%	6.62%	17,200	5,660	33.0%	5.60%
2002	28,100	11,400	40.4%	6.87%	20,800	6,840	32.8%	5.58%
2003	31,800	12,900	40.5%	6.88%	26,300	4,970	18.9%	3.21%
2004	38,000	16,100	42.4%	7.21%	33,900	7,650	22.6%	3.84%
2005	40,200	18,000	44.8%	7.62%	40,700	10,300	25.3%	4.31%
2006	42,800	18,100	42.3%	7.19%	45,200	13,300	29.3%	4.98%
2007	48,200	20,200	42.0%	7.13%	70,300	25,300	35.9%	6.11%
2008	57,100	24,300	42.6%	7.25%	44,500	10,000	22.5%	3.83%

Note: * The few prior-to-due-time debt repayments are excluded from the installment calculations. Source: HBS and authors' calculations. "At risk" is defined as an adjusted debt burden exceeding 30%. Frequency weights based on sampling weights are used to calculate the figures for the whole economy.

22 As described in the data section, unfortunately, we do not have the state variable with information on the total amount of loans a household has outstanding.

23 We construct the frequency weights from the sampling weights, normalizing them to sum to the total of approximately 4 million households.

24 This is the average default rate among overindebted households over the analyzed period 2005–2008. See subsection 5.3.

We see that the share of total annual debt service (installments) on loans of overindebted households is about 40% and rose slightly over the analyzed period, from 39.3% in 2000 to 42.6% in 2008. The corresponding share of total annual installments at risk of default is about 7%, starting at 6.7% in 2000 and reaching 7.3% in 2008. Again, to remind the reader, our definition of default is fairly broad, so that loans at risk should be regarded as loans at risk of having a missed payment in a given year. The real default rate is likely to be much lower, as only some of these loans will eventually default.

While we do not have any information about the share of total existing household debt that is at risk, we can see that, based on our data and our simulations, about 21.3% of the total amount of new loans in 2000 was given to households with an adjusted debt burden exceeding 30%.[25] The share of total new loans that are at risk varies substantially across the nine years, first going up by more than 10 percentage points in 2001 and 2002 and then dropping to about 19% in 2003, when the credit bureau came into use by five major banks. In 2003, the share of new loans to overindebted households started rising again, reaching a maximum of almost 36% in 2007. In 2008, when the financial crisis started, it fell back to 22.5%. The corresponding share of total new loans at risk of default ranges from 3.2% in 2003 to 6.1% in 2007. As the size of the household credit market has been rising, the absolute amounts of yearly debt service and of new loans have also increased. While risky installments more than doubled, from CZK 9.6 billion to CZK 24.3 billion, new loans given to households at risk in 2007 (CZK 25.3 billion) were five times as high as in 2000 (CZK 5.2 billion), but returned to their 2005 value of CZK 10 billion in the crisis year 2008.

6. Financial Stability and Regional Economic Shocks

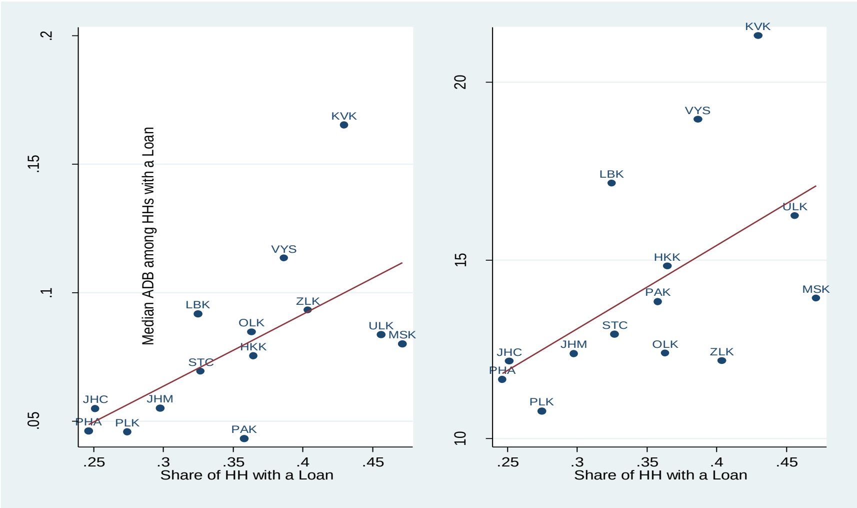
It has been well documented that there are substantial economic differences across regions in most EU countries, including the Czech Republic. It is therefore not surprising that the extent of borrowing, overindebtedness, and default vary geographically as well (see, for example, Vandone, 2007). The share of households with a loan ranged from around 25% in PHA and JHC to almost twice as high in ULK and MSK, the share of overindebted households ranged from 4.3% in PAK and 4.6% in PHA and PLK to 11.3% in VYS and 16.5% in KVK, and the median ADB among households with a loan ranged from 10.2% in PLK to 21.1% in KVK in 2008. Two regions had a share of overindebted households over 10% and 4 out of 14 regions had a median ADB over 15% in 2008.

Note that the low values of loan occurrence in the capital (PHA) are driven by the fact that we analyze all three types of loans. While PHA is the leading region in the share of households with a housing loan as well as with other loans, consumer loans, which turn out to

[25] Due to the already mentioned data limitations, the adjusted debt burden and the overindebtedness definition also include the part of installments paid in the current year on a new loan taken out in the same year. So the precise definition of households at risk of default is: households with an adjusted debt burden either exceeding 30% based on existing loans or exceeding 30% after taking out a new loan and accounting for installments paid on the new loan in the current year.

be widely used in other regions (possibly to make up for lower levels of income), render PHA as the region with the lowest loan occurrence in the population. The low level of indebtedness, on the other hand, is driven by the substantially higher income levels in PHA than other regions, and by the fact that the living minimum, as already discussed, does not vary across regions and therefore does not take into account regional differences in prices.

Figure 6.1: Borrowing and overindebtedness



Regions: PHA – Praha (Prague), JHC – Jihočeský (South Bohemia), PLK – Plzeňský (Plzeň), JHM – Jihomoravský (South Moravia), LBK – Liberecký (Liberec), STC – Středočeský (Central Bohemia), PAK – Pardubický (Pardubice), OLK – Olomoucký (Olomouc), HKK – Kralovĕhradecký (Hradec Králové), VYS – Vysočina (Vysočina), ZLK – Zlínský (Zlín), KVK – Karlovarský (Karlovy Vary), ULK – Ústecký (Ústí nad Labem), MSK – Moravskoslezký (Moravia-Silesia)

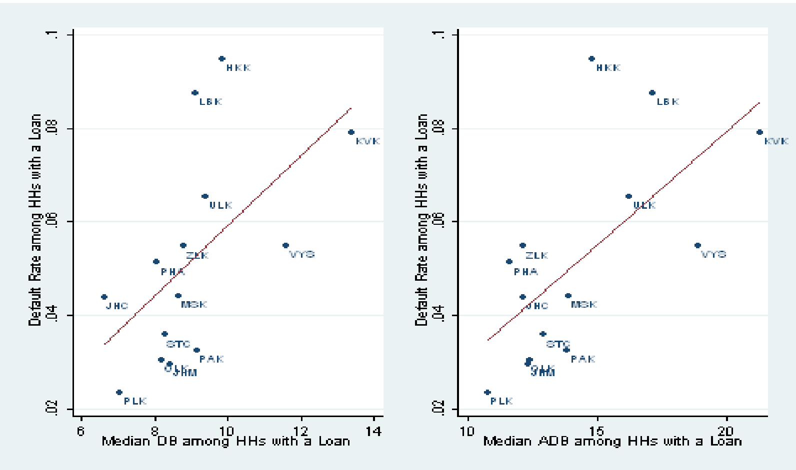
Figure 6.1 relates borrowing and overindebtedness at the regional level in 2008.[26] It suggests that there is a strong positive relationship between the share of households with a loan and the share of households with an adjusted debt burden of above 30%, as well as between the median debt burden among households with a loan and the share of households with a loan. The correlations are 0.62 and 0.55, respectively, both significant at the 5% level. It is evident from both scatter plots that overindebtedness increases with size of the credit market.

As the local household credit market is likely to be closely related to other local economic conditions, we next inspect the relationship between overindebtedness and key economic characteristics of the region. Specifically, we correlate the share of households with an ADB of greater than 30% to two key characteristics of the local labor markets – the unemployment rate and average household monthly income – across regions in 2008. While unemployment

26 In this section, we focus primarily on 2008, the most recent year available. The reasons are: (1) there has not been too much change across regions over recent years and the variation comes mostly from the cross-sectional dimension (across regions), (2) the 2008 data seems to be of the best quality, (3) our aim is to produce the most up-to-date results, and (4) we try to keep the figures easy to read. The results for previous years and for the values averaged over time show similar correlations as those for 2008.

and overindebtedness are positively contemporaneously correlated (correlation coefficient 0.52, significant at the 10% level), no such correlation exists at the regional level between households' overindebtedness and average monthly income in the region (possibly due to the two outlying regions PHA and STC, where the ADB is likely to be undervalued)[27] in 2008. A simple OLS regression of the share of households with an ADB of over 30% in the region on a constant regional unemployment rate in 2008 has an adjusted R2 of 0.27 and suggests that a 1% rise in the unemployment rate increases the share of overindebted households in the region by 0.9 percentage points. We next focus on the regional variation in the default rates and its relation to the observed overindebtedness, again by augmenting our data with information from the SILC dataset. In the previous section, we combined the two datasets using extrapolation at the household level. Here, we use a much simpler extrapolation: we use the default rates among households with a loan from the SILC data aggregated by year and region and merge it with the HBS data with information on the DB and the ADB, also aggregated by year and region.[28] The results are shown in Figure 6.2.

Figure 6.2: DB, ADB, and default rate among households with a loan in 2008



Regions: PHA – Praha (Prague), JHC – Jihočeský (South Bohemia), PLK – Plzeňský (Plzeň), JHM – Jihomoravský (South Moravia), LBK – Liberecký (Liberec), STC – Středočeský (Central Bohemia), PAK – Pardubický (Pardubice), OLK – Olomoucký (Olomouc), HKK – Kralověhradecký (Hradec Králové), VYS – Vysočina (Vysočina), ZLK – Zlínský (Zlín), KVK – Karlovarský (Karlovy Vary), ULK – Ústecký (Ústí nad Labem), MSK – Moravskoslezký (Moravia-Silesia)

Figure 6.2 focuses solely on households that have a loan and relates the regional default rates to the median DB and median ADB levels in 2008. First, we see that there is also substantial

27 PHA and STC represent the capital and the region surrounding it. While income in both regions is substantially higher than elsewhere (except for VYS), the cost of living also exceeds the levels in other regions, a fact which is, however, not reflected in our cost-of-living formula, which only varies with household size. Our ADB definition is therefore likely to undervalue the true adjusted debt burden in these two regions. If this was taken into account, the negative correlation between the adjusted debt burden measures and income might be reestablished.

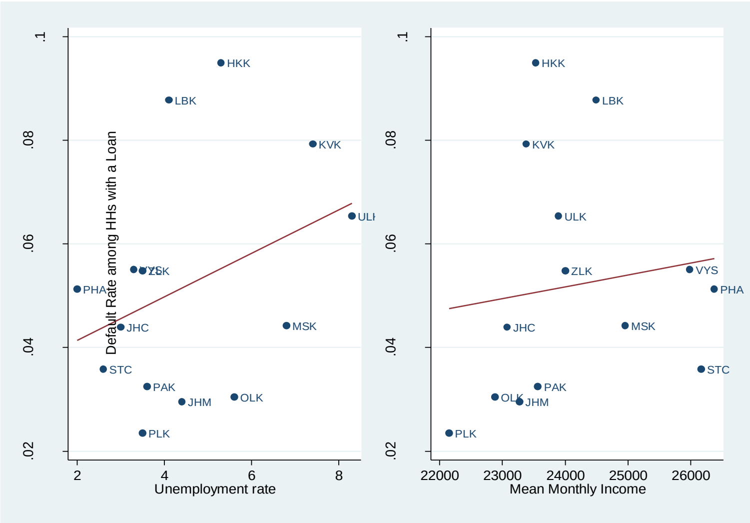
28 Again, we use the sampling weights in aggregation.

variation in default rates across regions and that it is closely related to the regional degree of indebtedness. In line with our previous findings, the correlation between the median ADB and default is higher (0.66) than the correlation between the median DB and default (0.57), both significant at 5%. While the regional level regression of the median DB on default in 2008 produces a fit of adjusted R2 = 0.27 in 2008, the adjusted R2 in the same regression using the median ADB is 0.39.

Finally, we relate the regional default rates to the local economic conditions in Figure 6.3. In accordance with our expectations, we see that unemployment and default are positively correlated. Surprisingly, there is also a slight positive relationship between average income and default. None of the two correlations, however, is significant. It is likely that economic shocks mostly affect repayments of households close to the edge of their ability to service debt and therefore increase the default rates only in regions where there is a high share of the overindebted.

An interesting question for assessing financial stability is whether negative economic shocks actually tend to hit regions with a high share of overindebted households more often than other regions, or, alternatively put, whether overindebted households, i.e., households with an adjusted debt burden exceeding 30%, tend to be concentrated in regions that are more vulnerable to negative economic shocks. In order to answer this question, we conduct the following exercise. We correlate the share of overindebted households (with a debt burden above 30%) in the population in 2008 and the unexpected shock that followed the year afterwards in the form of the global financial crisis. As the main consequences of the crisis were felt in the Czech Republic during 2009, we calculate the size of the shock at the regional level as the percentage point difference between the regional unemployment rate in the last quarter of 2009 and that in the last quarter of 2008. The results are shown in Figure 6.4. The bad news for financial stability is that the extent of overindebtedness is indeed somewhat positively correlated with economic vulnerability across regions, suggesting that regions with a higher average share of overindebted households in 2008 were hit harder by the negative consequences of the financial crisis in 2009 than other regions. The correlation coefficient is 0.43, significant at the 15% level.

Figure 6.3: Regional default rates and local economic conditions in 2008



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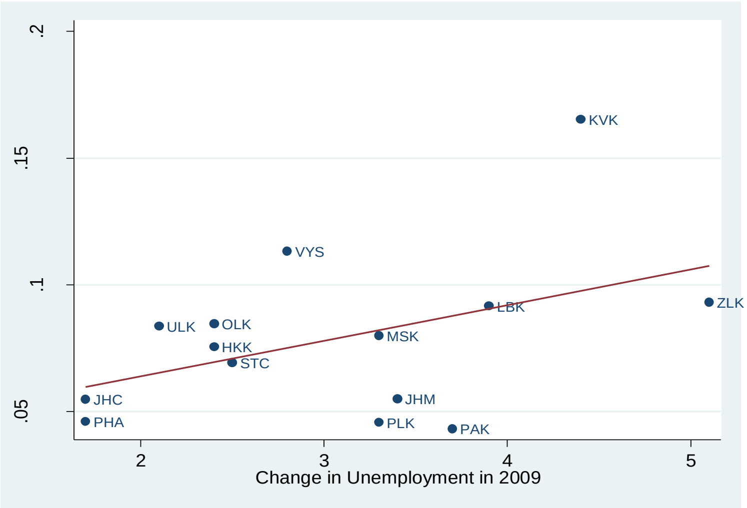
One might question to what extent the relationship between overindebtedness and future shock vulnerability that we have just presented is due to possible serial correlation in shocks and the fact that past economic shocks lead to overindebtedness through job losses and reduction in income.[29] We discussed the strong link between the past (and current) negative economic situation and excessive borrowing above when presenting the strong positive correlation between the current unemployment rate and the current extent of overindebtedness of 0.77 in 2008. However, the correlation between the 2008 unemployment rate and the future shocks defined above is only 0.12 and not significant even at the 20% level, suggesting that the regional variation in the consequences of the financial crisis was indeed rather unexpected.

We therefore conclude that, besides the obvious impact of negative economic shocks on the debt burden of households, it seems also to be the case that households with too high a debt burden are more likely to reside in regions that are more exposed to economic shocks. From the financial stability policy perspective, this finding suggests that the impact of future macroeconomic downturns on the default rate of households may be stronger than if the shocks were distributed evenly across regions.

[29] A reduction in income possibly affects both parts of the debt burden ratio, by directly decreasing the denominator and indirectly increasing the numerator if less income increases demand for loans and provided that households are granted these additional loans.

Figure 6.4: Household overindebtedness and unexpected negative economic shocks



Regions: PHA – Praha (Prague), JHC – Jihočeský (South Bohemia), PLK – Plzeňský (Plzeň), JHM – Jihomoravský (South Moravia), LBK – Liberecký (Liberec), STC – Středočeský (Central Bohemia), PAK – Pardubický (Pardubice), OLK – Olomoucký (Olomouc), HKK – Kralověhradecký (Hradec Králové), VYS – Vysočina (Vysočina), ZLK – Zlínský (Zlín), KVK – Karlovarský (Karlovy Vary), ULK – Ústecký (Ústí nad Labem), MSK – Moravskoslezký (Moravia-Silesia)

7. Conclusion

Loan growth is typically regarded as one of the early signals of financial tension. Household debt – and especially housing loans – contributed significantly to the growth of total loans over the last several years in the Czech Republic. The recent financial crisis has also highlighted the importance of understanding how households respond to various macroeconomic shocks and how this reaction depends on their income, demographic characteristics, and debt burden level. While this paper does not estimate the household loan repayment response to macro shocks directly, it is one of the first papers to use household level data to identify and characterize the households that are the most likely to default when affected by an adverse economic event. Household overindebtedness can have important implications for aggregate household spending (via the wealth channel) as well as for the financial system (via the balance sheets of the banking sector). As excessive household indebtedness may represent a financial and macroeconomic risk, analysis of household indebtedness provides important inputs for monetary policy as well as financial stability.

We have analyzed the evolution of the household credit market in the Czech Republic over the period 2000–2008. While the share of households that borrow remained stable and below 40%, the average amount of debt outstanding increased over the last decade relative to income. Credit growth was dominated by expansion of housing loans and also other loans, such as overdrafts, while the share of consumer loans among households decreased. Our analysis shows that the establishment of information-sharing through a credit bureau increased debt accumulation over the analyzed period rather than preventing it.

The debt burden – the ratio of annual loan repayments to annual net income – reached an average level of 10.5% among households with outstanding debt in 2008. We test the predictive power of the standard debt burden for default risk, where default is defined as the inability to make loan repayments on time. While this is a very conservative concept of default, it is the best information available in our data. We emphasize that all our results should be interpreted in the light of this broad definition. As typically only a fraction of loans with delayed payments become truly non-performing loans, both the default risk and the default rates are considerably overstated in our data, and should serve rather as a signal of potential future default.

We propose a new measure of debt burden – the so-called adjusted debt burden (ADB), which we define as the ratio of annual loan repayments to annual disposable income, where the latter is constructed as annual net income minus the living minimum corresponding to the household's size and composition.

Combining information from two data sources, we show that the adjusted debt burden is twice as strongly correlated with default as the standard debt burden. The default rate in the Czech Republic has declined since 2005, in contrast to the slightly rising standard debt burden measure, but in line with a similar decrease in the adjusted debt burden indicator.

We suggest that the adjusted debt burden rather than the debt burden should be used as a measure of default risk. In addition, we identify a cut-off point of an adjusted debt burden of above 30% to be the threshold above which the risk of default sharply rises. We propose to use "ADB above the 30% level" as the definition of overindebtedness when assessing potential threats to the financial stability of the household credit market. However, we acknowledge two potential drawbacks of our proposed measure. First, the living minimum used to calculate disposable income in the ADB does not vary across regions, whereas there clearly are regional differences in the cost of living in the Czech Republic. Second, a comparable definition of the living minimum is necessary for international comparisons. We leave these two issues for future research. We emphasize our general conclusion that the variation in the costs of living of households of different size and composition must be taken into account together with income when compared to the amount of repayments in order to assess households' default risk.

Based on our definition of overindebtedness, and extrapolating the HBS data to the whole economy, we estimate that overindebted households accounted for about 40% of repayments made and 33% (19%) of new loans taken out in 2007 (2008). This corresponds to about 7.3% of annual repayments and 6.1% (3.8%) of total new loans being at risk of default.

Finally, as one of the first papers on the household credit market, we explore the regional variation in households' borrowing and repayment behavior. We find substantial differences in overindebtedness and default across regions, which in turn are closely related to local economic conditions. We also show not only that financial stability in the whole economy is most affected by regions with the highest overindebtedness, but also that their contribution is likely to be augmented by the fact that these are also regions with a higher risk of negative economic shocks.

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Appendix:

A. Living Minimum

The living minimum we use for the calculation of discretionary income in the denominator of the ADB is set by the Czech Statistical Office (CZSO) and is available for each household in the data. It varies only by household composition, and as such it is calculated as a sum of all attributes concerning the given household. For example, the individual components for the calculation of the living minimum for 2005 are given below.

Child: below 5	1,720
6–9	1,920
10–14	2,270
15 or over	2,490
Other person	2,360
Household: Single member	1,940
2 members	2,530
3–4 members	3,140
5 or more	3,520

Source: HBS codebook.

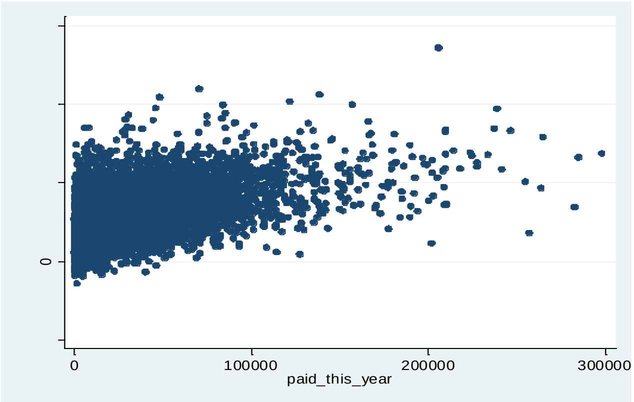
For example, in the case of a household consisting of a married couple with one child aged 4, the living minimum is equal to CZK 1,720 (child) + 2*CZK 2,360 (2 adults) + CZK 3,140 (household of 3 members) = CZK 9,580. For subsequent years, 5% annual growth is assumed for each component.[30]

B. Prediction Evaluation

Scatter plot of the observed values and fitted values of the loan amounts repaid from the HBS sample. The underlying regression output is available from the authors upon request.

[30] Note that a substantial change in the methodology that the CZSO uses for the living minimum calculation was made in 2007. Previously, the CZSO had provided information on the individual level and on the household level. Now, it provides figures on the individual level only. As we did not have the information to reproduce the past values of the living minimum according to the new methodology, we instead used the old methodology to calculate the living minimum in 2007 and 2008 in order to preserve comparability over time, increasing the living minimum by 5% each year (as done by the CZSO for the years preceding 2007).

Figure B.1



C. Analysis of Cut-off Points for Overindebtedness

Table C.1: SDB and ADB cut-off points for the 20 income quantiles

Quantile	Standard debt burden	Adjusted debt burden
1	3,855698	5,491145
2	5,658011	8,265864
3	6,477815	9,826997
4	7,173244	11,04217
5	7,709298	12,10995
6	8,16185	13,11709
7	8,666596	14,10531
8	9,217764	15,14901
9	9,704064	16,21622
10	10,23463	17,30828
11	10,80744	18,44758
12	11,35599	19,64429
13	11,99717	20,97653
14	12,60664	22,51557
15	13,26491	24,60589
16	13,99034	27,22987
17	14,89989	31,09706
18	16,1423	38,50175
19	18,24358	58,54531
20	27,03436	99,44116

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