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Household Loan Repayment Difficulties after the Payment Moratorium – Hungarian Experience from the Covid-19 Pandemic*

Ákos Aczél – Nedim Márton El-Meouch – Gergely Lakos – Balázs Spéder

We examine the relationship between the widespread, long-lasting debt forbearance on household loans introduced in Hungary at the outbreak of the coronavirus pandemic and subsequent loan repayment difficulties. We estimate linear probability and logit models at the contract level. Although our method is not suitable for identifying causal effects, participation in the moratorium proves to be a strong predictor of subsequent defaults. This is true even if we take into account the wide range of relevant factors observed at the end of the general moratorium period (October 2021). Our main results show that contracts which left the general moratorium at the end of the moratorium and, within this, those that took full advantage of the programme, were on average 3.2 and 4.2 percentage points more likely to become non-performing in September 2022 than those that never participated in the moratorium. This relationship can explain almost half of the differences in default rates between the respective groups.

Journal of Economic Literature (JEL) codes: D12, D14, G28, G51

Keywords: payment moratorium, household loans, credit risk, non-performing loans, credit registry, coronavirus pandemic

1. Introduction

Immediately after the outbreak of the coronavirus pandemic, many countries introduced temporary, but widespread relief of household loan repayments[1] to contain the anticipated large liquidity shocks during the pandemic that could lead

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[1] The IMF has compiled the economic responses of 197 countries during the coronavirus pandemic until July 2021: https://www.imf.org/en/Topics/imf-and-covid19/Policy-Responses-to-COVID-19. More detailed ESRB collection for European countries: https://www.esrb.europa.eu/home/search/coronavirus/countries/html/index.en.html.

to systemic household debt repayment difficulties. The payment difficulties of indebted households can have large-scale, negative external effects on the real economy (*Mian – Sufi 2014*). As a result of the Global Financial Crisis, the level of non-performing household loans also increased significantly in Hungary from 2009 onwards (*Figure 1*), which has greatly restrained and prolonged economic recovery (*Verner – Gyöngyösi 2020*).

The payment moratorium was not a widespread macroeconomic crisis management tool in the past, so only a few empirical studies have been carried out to measure its effects. The first widespread, international use of this kind of payment moratorium was justified by the following circumstances. First, the crisis was not triggered by an economic shock (but by a pandemic), and thus it was expected that economic actors would face liquidity challenges rather than solvency problems. In the case of an economic crisis caused by a pandemic (not an overwhelming one), there was hope that once the pandemic had passed, the previous economic processes could be restored relatively quickly, without major systemic changes. Second, there was no fear that the moratorium would encourage irresponsible indebtedness in the future (moral hazard), as the crisis was not caused by excessive financial risk-taking. Third, by that time there were both theoretical and empirical arguments that the adverse spill-over effects of household debt problems are better avoided by temporary, but immediate payment relief (liquidity support), rather than by permanent but not necessarily immediate relief (debt relief).[2]

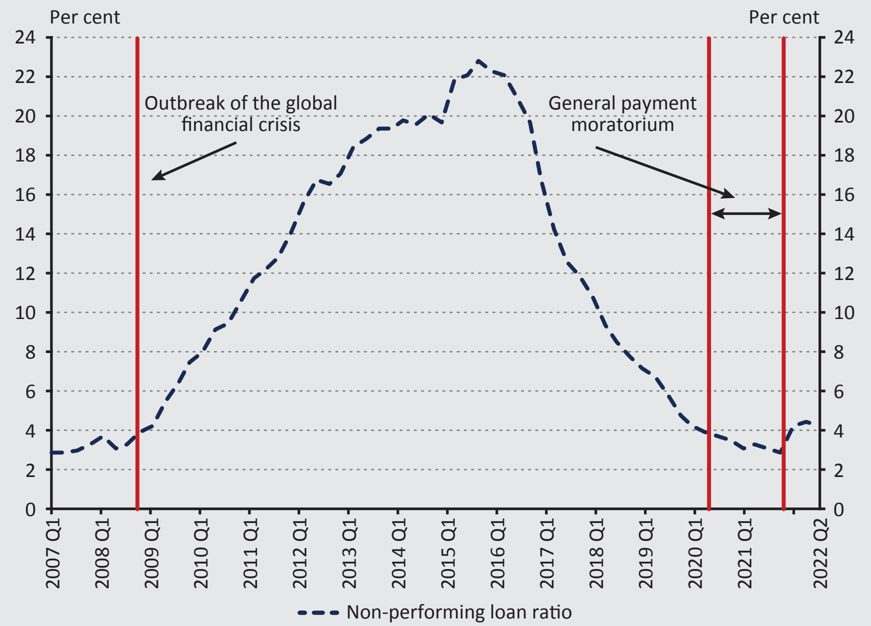
Studying the Hungarian household payment moratorium can provide useful insights, as it was considered a significant intervention even by international standards. Based on a comparison of moratoria introduced in 23 EU countries, *Drabancz et al.* (*2021*) found that, like in many other countries, Hungary introduced a programme that was mandatory for banks and covered both principal and interest payments, whereas few countries introduced an unconditional, long-lasting programme like the Hungarian one, and it was only in Hungary that contracts were automatically included (opt-out logic).[3]

In this study, we use data from Hungary to explore whether participation in the general payment moratorium is relevant to the subsequent development of household loan repayment difficulties. A well-functioning payment moratorium effectively supports managing the liquidity shock to households, after which the programme can be terminated without significant debt repayment difficulties. In Hungary, household loans disbursed until 18 March 2020 were unconditionally eligible for the moratorium until 31 October 2021, which then became conditional from November 2021. After the general payment moratorium period, the ratio of

[2] See, for example: *Eberly – Krishnamurthy* (*2014*), *Ganong – Noel* (*2020*), *Campbell et al.* (*2021*) *and Boar et al.* (*2022*).
[3] For more details, see: *EBA* (*2020*) and *ESRB* (*2021*).

non-performing loans increased significantly, from 2.8 per cent in Q3 2021 to 4.2 per cent in Q4 2021 (*Figure 1*). This is nowhere near the level of the corresponding period after the outbreak of the Global Financial Crisis, i.e. roughly in 2010–2011.

Figure 1
Ratio of non-performing household loan portfolio in the credit institution sector



Note: The definition of non-performing loans changed in 2015. From then on, in addition to loans over 90 days past due, loans less than 90 days past due where non-payment is likely are also classified as non-performing. Calculated by clients until 2010 and by contracts from 2010.

Source: MNB (2022): Figure 48

The strength of our approach is that we can use detailed monthly observations of loan contracts at the individual level. Our main result is that the moratorium track record is non-linearly related to non-performance in September 2022, even when we take into account numerous relevant individual loan and debtor characteristics observed in October 2021. Our estimation using a linear probability model suggests that contracts which participated in the general moratorium for a moderate length of time at most, or exited before the end of the programme have on average roughly the *same* probability to become non-performing later on as contracts that opted out of the moratorium altogether. However, the probability of non-performance for contracts that left the general moratorium at the end, and within this group, for loans that took full advantage of the programme, is on average 3.2 and 4.2 percentage points *higher*, respectively. These latter values are significant because they can explain almost half of the differences in non-performing ratios between the respective groups.

It is important to stress that the method we use is not suitable for identifying the causal effect of the general payment moratorium on payment problems after the end of the programme. Indeed, we cannot be sure that participation in the moratorium and subsequent default are not related to other relevant circumstances that are difficult to observe. Partly for this reason, we cannot determine exactly why the described correlation between moratorium participation and subsequent credit risk exists. One possibility is that intensive participation in the moratorium is the result of self-selection, which is more likely to be chosen by debtors with poorer liquidity or solvency. Another possible explanation is that the moratorium weakens incentives to maintain or restore the ability to repay debts.

The public policy relevance of our results is the following. After systemic, voluntary, and temporary payment relief programmes, an increase in the ratio of non-performing loans associated with the programme can be expected, although to a limited extent. Prudential regulation of credit institutions, as well as loan loss provisioning at individual credit institutions, should also take into account that participation in the programme is itself a strong predictor of defaults within one year.

The topic of our study is most closely related to the nationwide experiment in India by *Fiorin et al.* (*2022*), starting in late 2020, in which they investigate the effects of a payment moratorium on delinquent consumer loans and find that the moratorium does not worsen the chances of loan repayment after the programme. To our knowledge, none of the studies examining the effects of the household payment moratoria introduced during the coronavirus pandemic have looked in detail at the relationship between the programme and subsequent difficulties in repaying loans so far. *Noel* (*2021*) argues that such measures in the US were better designed than similar measures during the Global Financial Crisis. Looking at individual loan data, *Cherry et al.* (*2022*) find that the programmes were successful in limiting household loans from becoming non-performing during the pandemic and complemented other crisis management measures well. *Capponi et al.* (*2021*) estimate the effect of these measures on household lending (specifically mortgage refinancing). *Kim et al.* (*2022*) estimate causal effects using loan-level household mortgage data and find that the moratorium mostly reached those in need, without serious unintended side effects. The effect of the pandemic and the household payment moratorium on inequality is examined by *An et al.* (*2022*). *Gerardi et al.* (*2022*) comprehensively assess all pandemic-related measures that targeted the US mortgage market, focusing primarily on minorities. The moratorium on student loans significantly increased consumption in the short run, but also increased indebtedness in the longer run by taking out other types of household loans, as found by *Dinerstein et al.* (*2023*). *Katz* (*2023*) compares the effects of the student loan moratorium and fiscal stimulus payments during the pandemic on consumption and savings.

Albuquerque – Varadi (*2022*) estimate the effect of the UK's mortgage payment holidays on consumption from transaction-level spending data. *Allen et al.* (*2022*) look into the reasons for low participation in the Canadian loan deferral programmes and emphasise the role of awareness and easy access. Based on survey data, *Allinger – Beckmann* (*2021*) analyse household enrolment in payment moratoria in ten Central European countries (including Hungary) and the relationship of the moratorium to payment difficulties. The initial experience of the payment moratorium on household loans in Hungary is described by *Drabancz et al.* (*2021*), while the factors that make participation more likely are analysed by *Dancsik – Fellner* (*2021*) and *Berlinger et al.* (*2022*).

The paper is structured as follows: *Section 2* describes the data. In *Section 3* we present a linear probability model examining the relationship between moratorium track record and subsequent non-performance. We show our results in *Section 4* and their robustness in *Section 5*. The final section concludes.

2. Data

2.1. The database

We needed loan-level observations of all existing credit and leasing contracts of Hungarian households at the end of October 2021.[4] These were obtained from four data sources. We narrow our analysis to loans granted by Hungarian credit institutions, which is not a significant simplification, as the vast majority of Hungarian household loans are of this type. The variables used are presented in *Table 3* in the *Appendix*.

Most of the characteristics of loans are taken from the credit registry of the Magyar Nemzeti Bank (HITREG), which has been operational since 2020 and contains detailed monthly data on all outstanding household loans of credit institutions. Older characteristics related to loans (e.g. whether the debtor was previously delinquent, whether the loan was previously foreign currency denominated) are obtained from a data report to the central bank that has the same data content as the Central Credit Information System. We can identify credit history characteristics for more than 90 per cent of the contracts.

Income data are derived from two sources. First, we use one twelfth of the gross annual income of debtors included in the consolidated tax base in the personal income tax returns of the National Tax and Customs Administration, which can be identified for roughly 70 per cent of loans. We use this income data only for the imputed debt service-to-income ratio for loans taken out before 2015, as this indicator is not

[4] For simplicity, all contracts are referred to as loans in the following.

available before the introduction of the debt cap rules.[5] We calculate other income data from the pension contributions database of the Hungarian State Treasury. Derived gross monthly incomes are less accurate on an annual basis, but measure more precisely the evolution of incomes at the beginning of the pandemic, i.e. between March and December 2020. ISCO codes describing tasks and duties of the debtor's job are also derived from here, and are used with only single-digit precision, as more detailed classifications give very similar results. Data from the pension contributions database can be matched with varying success to our other data by loan type: roughly 70 per cent for housing loans and prenatal baby support loans, just under 60 per cent for personal loans, and for less than half of overdrafts and credit cards.

Table 1
Development of outstanding debt between October 2021 and September 2022 by loan type

		2021			2022								
		Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep
Housing	(HUF bn)	4,556	4,540	4,486	4,413	4,355	4,289	4,231	4,169	4,095	4,042	3,987	3,953
	(thsnd pcs)	694	686	678	667	659	648	639	631	620	613	605	600
Home equity	(HUF bn)	799	791	777	752	740	725	712	698	678	667	656	658
	(thsnd pcs)	187	184	181	177	174	170	168	165	161	159	157	157
Prenatal baby support	(HUF bn)	1,501	1,496	1,490	1,416	1,411	1,405	1,399	1,393	1,387	1,380	1,373	1,431
	(thsnd pcs)	160	160	160	152	152	152	152	152	152	152	151	158
Personal	(HUF bn)	1,138	1,111	1,080	1,016	986	958	931	904	879	855	832	844
	(thsnd pcs)	804	787	770	730	715	697	682	667	652	638	624	633
Vehicle	(HUF bn)	157	151	146	141	135	128	124	119	114	110	106	102
	(thsnd pcs)	94	92	90	87	85	81	79	77	75	72	71	68
Hire purchase	(HUF bn)	27	25	23	21	19	18	16	15	13	12	11	10
	(thsnd pcs)	240	230	212	199	188	178	168	158	148	138	129	121
Overdraft	(HUF bn)	196	190	185	191	162	170	171	177	180	171	168	175
	(thsnd pcs)	1,769	1,689	1,679	1,662	1,652	1,641	1,630	1,621	1,603	1,590	1,570	1,566
Credit card	(HUF bn)	159	158	158	148	143	139	137	140	137	134	134	132
	(thsnd pcs)	1,364	1,346	1,325	1,296	1,275	1,248	1,224	1,204	1,184	1,165	1,134	1,118
Other	(HUF bn)	556	538	516	490	465	408	399	393	363	348	329	314
	(thsnd pcs)	36	35	33	32	32	31	30	30	29	28	28	27
Total	(HUF bn)	9,089	8,999	8,863	8,587	8,417	8,240	8,120	8,007	7,848	7,720	7,596	7,619
	(thsnd pcs)	5,347	5,209	5,128	5,003	4,932	4,846	4,771	4,706	4,623	4,556	4,470	4,449

Note: In a given month, only loans with data for outstanding debt, which can be as low as zero, are included. Lombard loans make up a significant part of the other category, with HUF 260 billion outstanding debt in October 2021.

[5] For more on the debt cap rules, see Footnote 16.

We exclude contracts for which it cannot be determined whether they remained in moratorium after October 2021, as well as those contracts that existed between March 2020 and October 2021 but lacked a moratorium classification at some point during that period. We also disregard the very small number of contracts where the primary borrower is not a resident in Hungary or does not live in Hungary. For a small number of the remaining contracts, there are no observations on the outstanding debt from October 2021 to September 2022, which are also ignored. For many other variables, we use slightly cleaned data. Altogether, data cleaning operations exclude 1–2 per cent of observations from the analysis.

Due to the initial uncertainties in the data reporting on moratorium status, we disregard the March 2020 classifications, which excludes the time spent in moratorium in the second half of March. In the end, we cover 5.3 million contracts with credit institutions, to which a total of HUF 9,089 billion (around EUR 25.2 billion at the time) of outstanding debt was linked in October 2021. This stock has steadily decreased over time, due to maturing loans (*Table 1*).[6]

2.2. Participation in the general payment moratorium

Participation in the general payment moratorium could be varied, so after describing the programme, we first look at which debtors took advantage of the moratorium, when and for how long, for which loans. In *Section 2.3*, we follow the development of payment difficulties of loans from June 2021 to September 2022 for three subgroups: debtors who voluntarily left the general moratorium, debtors who exited the programme at the end of the moratorium and debtors who never participated in the moratorium.[7] The methodology and results of the detailed analysis of the relationship between the moratorium track record and subsequent payment difficulties are presented in *Sections 3* and *4.*

All principal, interest and fees on household loans disbursed by 18 March 2020 were automatically granted debt forbearance, initially until 31 December 2020 and, after several extensions, until 31 October 2021.[8] Debtors could simply indicate their intention to leave the moratorium and were also free to opt in and out again. From November 2021, only clients with permanently reduced income, those who were unemployed, were employed in public work scheme, raised children or were retired could remain in the programme, and this had to be requested. If a debtor had exited a contract after October 2021, it could no longer be re-admitted to

[6] On one or two occasions, the number of loans and the total outstanding debt for certain types of loans may increase slightly over time rather than decrease. This is due to missing observations in the database and is of negligible importance for our analysis.

[7] The remaining contracts are those that have also opted in to the conditional moratorium from November 2021.

[8] In the study, the eligible households are identified by the more precisely observable contracting date rather than by the date of disbursement. In this way, we classify a slightly larger stock than the actual eligible loan stock as eligible.

the programme, which ran up until 31 December 2022. During the period in the moratorium, the debt continued to accrue interest, but repayment of this interest only had to be started after exiting the moratorium, in equal annual instalments over the remaining term. The main rule, however, was that the total monthly instalment to be paid could not increase after leaving the moratorium; instead, the remaining maturity of the loan could be extended.

36 per cent of household loans existing in October 2021 (47 per cent of eligible loans) participated in the general payment moratorium, representing 41 per cent of the outstanding debt stock (66 per cent for eligible loans). The aggregate utilisation of the general payment moratorium has declined monotonically over time (*Figure 2, left panel*).[9] 12 per cent of the loan contracts existing in October 2021 had exited the moratorium earlier, followed by a further 21 per cent at the end of October, leaving not even 3 per cent in the conditional moratorium.[10] Not even a tenth of all contracts spent at least two separate periods in the general moratorium, both in terms of number of loans and volume of outstanding debts. We think that the actual ratio is even lower, because in some months, for some credit institutions and for some loan types, there are outliers in the number of loans opting out or in, which suggests some minor inaccuracy in the measurement of the time spent in moratorium. This happens occasionally for more than 10,000 contracts, in total affecting only a few per cent of the roughly 1.9 million contracts that were subject to the moratorium.[11]

We see that there is a significant group of debtors who decided themselves to leave the general moratorium, and a more numerous group left in October 2021, many of them involuntarily, after participating for a fairly long period. Although the number of early exits is much smaller, their outstanding debt stock in October 2021 is close to that of those who exited in October: HUF 1,493 billion vs. HUF 1,714 billion (*Figure 2, right panel*). The distributions of their outstanding debt by loan type show significant differences. Among those exiting before the end of the programme, the proportion of housing loans is significantly higher, while personal loans are more common in the other group.

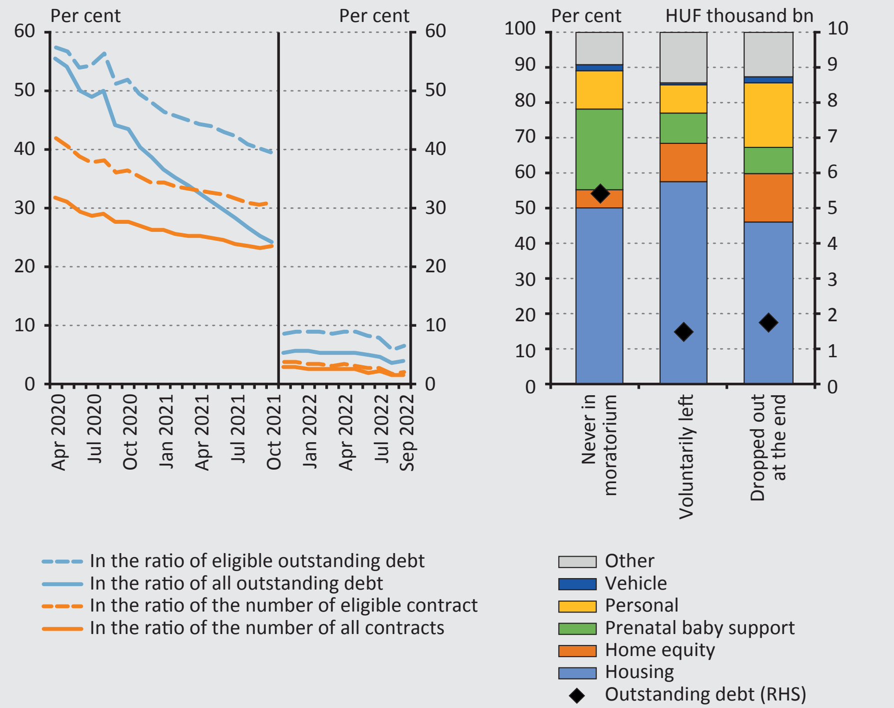
[9] The different development of the curves in *Figure 2* is not only influenced by the different development of the participation but also by the different development of the denominators: The outstanding debt of eligible contracts decreases over time due to the amortisation of the part not in moratorium, while the debt stock of all contracts increases due to the expansion of the loan disbursements after 18 March 2020 in excess of the amortisation of loans outstanding.

[10] Considering volumes, 16 per cent, 19 per cent and almost 6 per cent are obtained if the outstanding debt as of October 2021 is used for the weighting.

[11] In the regression analyses in *Section 4*, we also use the indicator variable of multiple opting in the general moratorium, which we interpret at least partly as a sign of measurement error of the time spent in the moratorium.

The outstanding debts of those who did not participate in the moratorium are three to four times higher than these, and prenatal baby support loans in particular are over-represented, in part due to the fact that a significant proportion of them are relatively new loans and thus not eligible for the moratorium.

Figure 2
Loans in payment moratorium: ratio and composition by loan type



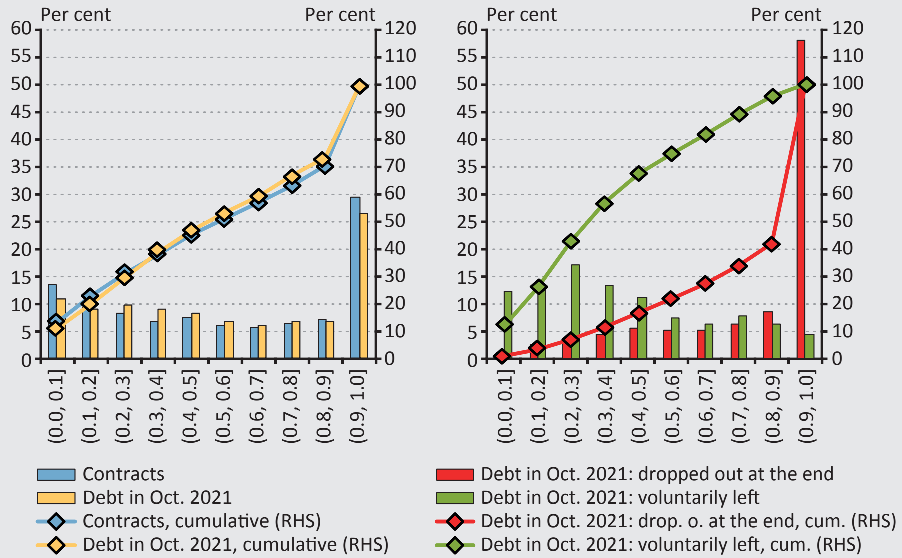
Note: The left panel shows the ratios within the contracts existing in October 2021, always calculated with the current outstanding debt. The right panel shows the distributions of the outstanding debt in October 2021 of contracts existing in October 2021 by loan type for groups with different moratorium track records. Never in moratorium: They have never been in moratorium. Voluntarily left: They left the moratorium before October 2021. Dropped out at the end: They dropped out of the moratorium at the end of October 2021.

A more accurate classification of moratorium history can also be constructed, which takes into account the length of time the primary borrower has been in moratorium with different loans having different instalments. To measure the intensity of participation in the general payment moratorium, we use the following definition: For each debtor *j*, we assign a value between 0 and 100 per cent by taking into account all their contracts indexed by *i* according to whether there was a debt forbearance in force for the instalments of that contract in month *t*:

$$Moratorium\ intensity^{j} = \frac{\sum_{t=Apr.\,2020}^{Oct.\,2021} \sum_{i} instalment_{i,t}^{j} * in\ moratorium_{i,t}^{j}}{\sum_{t=Apr.2020}^{Oct.2021} \sum_{i} instalment_{i,t}^{j}}$$

30 per cent of the primary borrowers of contracts participating in the general moratorium at most who have positive moratorium intensity have almost fully taken advantage of the moratorium, while roughly half of them have a utilisation rate below 50 per cent (*Figure 3, left panel*). More than half of the primary borrowers exiting the programme at the end of October 2021 were in moratorium almost throughout, while those who voluntarily left earlier have a typical intensity of less than 50 per cent (*Figure 3, right panel*).

Figure 3
Distribution of contracts that participated in the general moratorium at most by intensity of participation of the primary borrower



Note: The left panel shows the distribution of the contracts that participated in the general moratorium or never participated, but have a main debtor with positive moratorium intensity. For the primary borrower of a contract, the intensity of participation in the moratorium is measured by the proportion of his/her total payment obligations during the general moratorium period deferred by the moratorium. Voluntarily left: They left the moratorium before October 2021. Dropped out at the end: They dropped out of the moratorium at the end of October 2021.

2.3. Defaults at the end of the general payment moratorium

Debt service obligations of the contracts subject to the moratorium were temporarily suspended, which also ruled out the possibility of becoming delinquent. However, the accounting rules continued to require credit institutions to classify contracts into different categories (stages) for loan loss provisioning purposes, depending on the foreseeable future loss they may incur in relation to the contracts. They could also assign a non-performing status if they had reasonable grounds to believe that, without the protection of the moratorium, the debtor would be unlikely to pay. The delinquency of clients that entered into moratorium with pre-existing delinquency remained unchanged for the duration of the moratorium and could only increase after exiting the programme.

In this paper, we consider the non-performing classification (performing vs. non-performing) of credit institutions as the main indicator of payment difficulties. In our view, this rating makes the most accurate use of the wide range of relevant circumstances, as credit institutions seek to use a variety of information in the rating process, including information that is not available to outsiders.

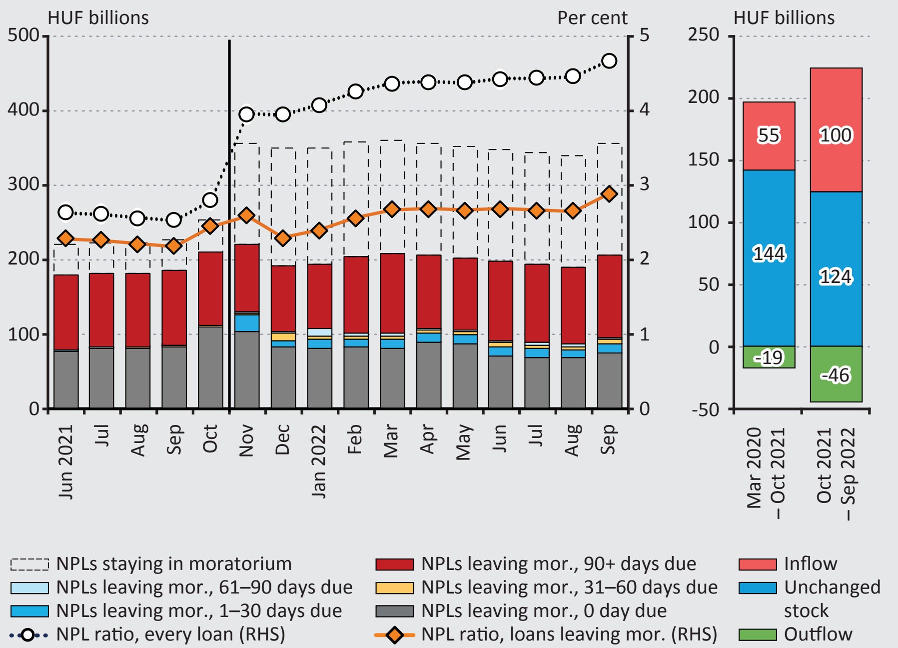
One of the possible alternatives is the extent of delinquency. This is not used because delinquency per se is insensitive to other relevant elements of payment difficulties, such as the size of delinquent amount. Another possibility could be some version of probability of default, but such a probability is difficult to define accurately, and the credit registry does not reliably contain such data for all institutions. Nevertheless, the non-performing classification has the disadvantage that a loan can be removed from the non-performing status even if the debtor's solvency has not actually improved (for example, by selling the loan). We do not have good enough data to identify such outflows, but we try to mitigate their impact. Therefore, for any loan maturing after September 2022 that was missing a September 2022 non-performing classification, we impute the classification for each of the months missing until September that was contained in the last data observed in a previous month.[12] The change does not substantially alter the results of the regression analysis.

Among all contracts existing in October 2021, the ratio of non-performing loans jumped from 2.8 per cent at the end of the general payment moratorium in October to 4.0 per cent in November, and then rose slightly further (*Figure 4, left panel*). The increase was mostly related not to contracts that left the general moratorium but to those that remained in the moratorium. In November, banks classified 28 per cent of outstanding debts of loans that remained in moratorium as non-

[12] We do not make changes to overdraft and credit card loans. Without them, there are 230,000 loans that have some kind of non-performing classification in October 2021, but do not have one in September 2022, even though the loan will not mature until later.

performing, up from 9 per cent in October. This was presumably due to the fact that the rules had extended the programme only for vulnerable groups, and that they had to apply for it, which may have indicated poorer solvency. The non-performing ratio excluding those who remained in the moratorium barely increased after the general moratorium (2.4 per cent in October 2021 and 2.9 per cent in September 2022) and thus remained much lower than for those opting for the conditional moratorium.[13] The non-performing stock in this group was around HUF 200 billion in the months after the end of the general moratorium, half of which was delinquent beyond 90 days. Behind this broadly unchanged stock over time, there was a larger inflow and outflow in 11 months than in the 19 months of the general moratorium (*Figure 4, right panel*). This suggests that a significant amount of meaningful additional information may have been used in the non-performing classifications after the general moratorium ended.

Figure 4
Non-performing household loan portfolio by delinquency and migration

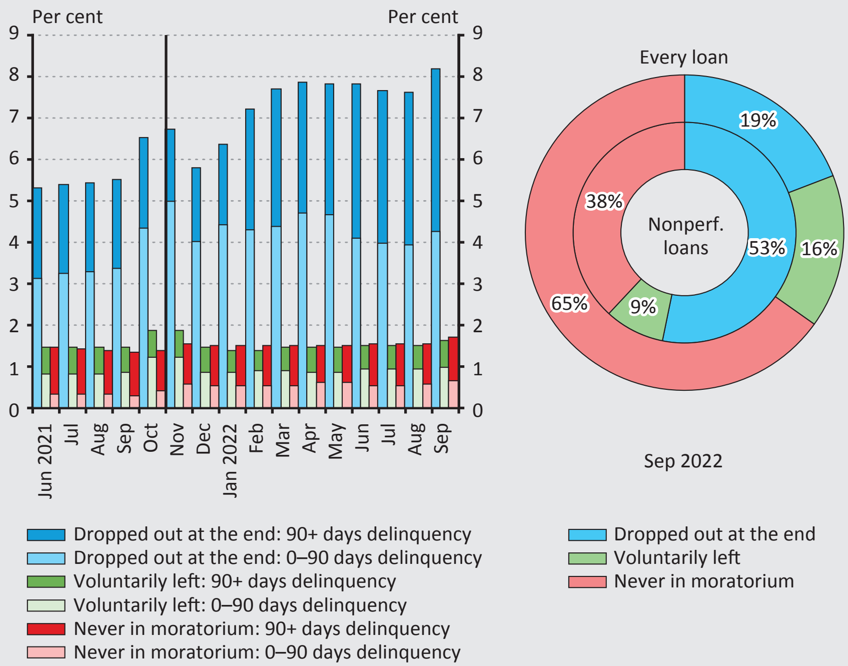


Note: The left panel shows the volume and the share of non-performing loans within the outstanding debt at the given date of loans existing also in October 2021. The right panel shows the transitions between March 2020 and October 2021 and between October 2021 and September 2022 of the stock of non-performing loans within the loans that left the moratorium in October 2021 at the latest. It takes into account only the loans with observable non-performance classifications both at the beginning and at the end of the given period, and it calculates with the outstanding debt in October 2021.

[13] A credit institution classified a portfolio of HUF 26 billion as non-performing in October and then reclassified most of it as performing in December. Without this, the temporary increase in the ratio of non-performing loans observed in October and November would disappear.

Both the typical levels of non-performing ratios and their evolution around the end of the general payment moratorium differ significantly depending on whether and, in particular, how loans have previously participated in the moratorium. Interestingly, the non-performing ratio among those that did not participate in the moratorium and those that exited the general moratorium before its end were similarly low, between 1.5 and 2.0 per cent around the end of the programme (*Figure 5, left panel*). The non-performing ratio was much higher among those that dropped out of the general moratorium in October 2021. This group is so overrepresented in the stock of non-performing loans that it accounts for more than half of it (*Figure 5, right panel*).[14]

Figure 5
Non-performing household loan portfolio by delinquency and participation in the general payment moratorium

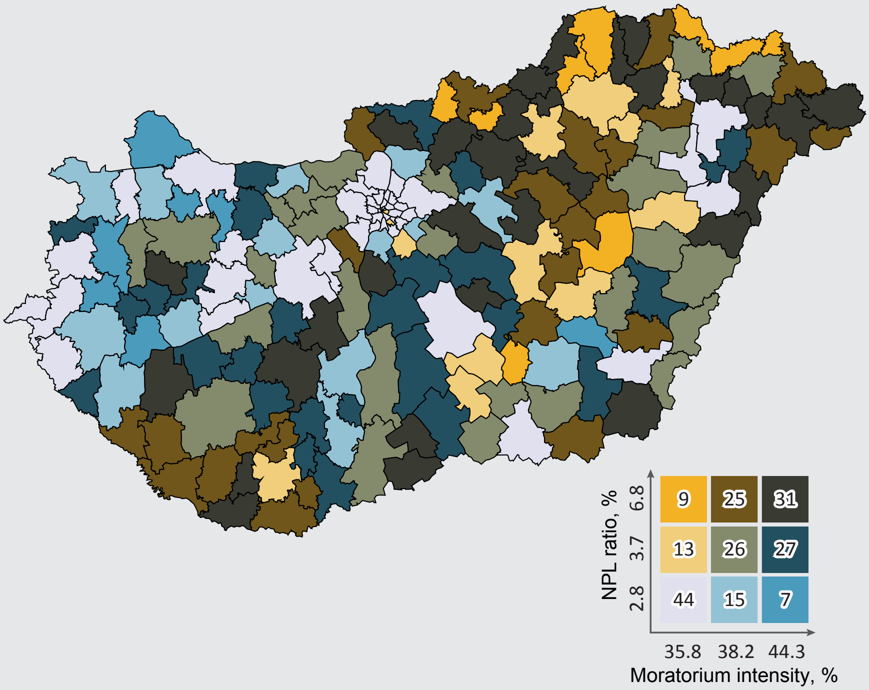


Note: Only household contracts existing in October 2021 are shown. Dropped out at the end: They dropped out of the moratorium at the end of October 2021. Voluntarily left: They left the moratorium before October 2021. Never in moratorium: They have never been in moratorium. In the left panel, ratios of non-performing loans are shown within outstanding debts at the given date, the non-delinquent but non-performing stock is classified as "0–90 days delinquency". The right panel calculates with outstanding debts in September 2022.

[14] In the following, we regress the September 2022 non-performing classifications of individual contracts; therefore, in addition to the usual volume-based assessment of non-performance, the contract number-based one may be of interest. Having done this, the results obtained are very similar to the ones seen in *Figure 4* and *5*.

The positive correlation between the intensity of participation in the moratorium and subsequent non-performance is also observed at the district level. The correlation coefficient is relatively high: 47 per cent (*Figure 6*). In larger cities, moratorium intensity and non-performance rates in September 2022 are also typically among the lower ones. At the other extreme are the least urbanised districts of the south-western and eastern part of the country, where both indicators typically take high values. It is also noticeable that in almost all of the country's north-western districts, the ratio of non-performing loans is typically relatively low.

Figure 6
Participation in the general payment moratorium and subsequent ratio of non-performing household loan stock by district



Note: The map does not take into account household loan contracts existing in October 2021 that remain in moratorium in November, nor does it take into account those contracts where the primary borrower could have applied the moratorium on a total instalment of more than HUF 20 million (around EUR 56,000 at the time) on all loans during the general moratorium. The horizontal axis of the legend shows moratorium intensity aggregated at district level. The vertical axis shows the non-performing share of the district-level outstanding debt in September 2022. The numbers on the axes are the tercile values separating each category and the maximum. The squares contain the number of districts in each category.

3. Method

We use regression analysis to examine how much of the correlation between more intensive participation in the moratorium and a higher probability of subsequent non-performance can be explained by usual risk factors that contribute to defaults. For ease of interpretation, simple linear probability models are estimated at the contract level. For the estimations, we use household loans that existed in October 2021 and left the programme until the end of the general payment moratorium or never participated in it.

The dependent variable is always the binary variable encoding the non-performing classification in September 2022, which takes the value 0 if the given loan is performing and 1 if it is non-performing. Our main explanatory variable is participation in the moratorium, which is measured in two ways as discussed in the previous section. First, we use a threefold classification (those who dropped out of the general moratorium in October 2021, exited earlier or never participated in the moratorium) and second, we apply a category variable composed of 11 values from the moratorium intensity, which divides the possible values by 10 per cent in addition to zero. The explanatory variables include a number of characteristics of the contract and the primary borrower, a detailed list of which is provided in *Table 3* in the *Appendix*. We use observations of the explanatory variables in October 2021, i.e. we examine the extent to which these variables at the end of the general payment moratorium can predict non-performance in September 2022. The estimation results do not allow us to identify *casual effects* between the moratorium and subsequent non-performance, as we cannot be sure that participation in the moratorium and subsequent default are not related to other important circumstances that cannot be observed.[15]

In total, we estimate eight model specifications, four with the threefold moratorium participation variable and four with the moratorium intensity variable. In both groups, we include the same explanatory variables in several waves. Each model is estimated on the same subsample, which is as extensive as possible containing observations on all explanatory variables applied. This covers nearly half of the observations in the database. In order not to reduce our sample too much, the explanatory variables with the fewest observations are omitted from the baseline analysis. However, robustness checks also include an analysis with these variables.

[15] Examples include risks regarding private life and health, time preferences, the extent of bounded rationality, or efforts to maintain or improve solvency.

4. Results

Table 2 presents the main results. The explanatory variables that are included step by step reduce the estimated coefficients of the participation in the general moratorium. However, these coefficients remain significant even after applying all of the control variables, regardless of the measure for moratorium participation [regressions (4) and (8)]. According to regression (4), contracts that exited from the general moratorium at the end of the programme are on average 3.2 percentage points more likely to become non-performing in 11 months compared to those that never participated in the moratorium. This relationship can explain almost half of the difference in non-performing ratios between the two groups. However, leaving the general moratorium earlier predicts 0.1 percentage points lower probability of non-performance on average compared to loans that never participated in the moratorium.

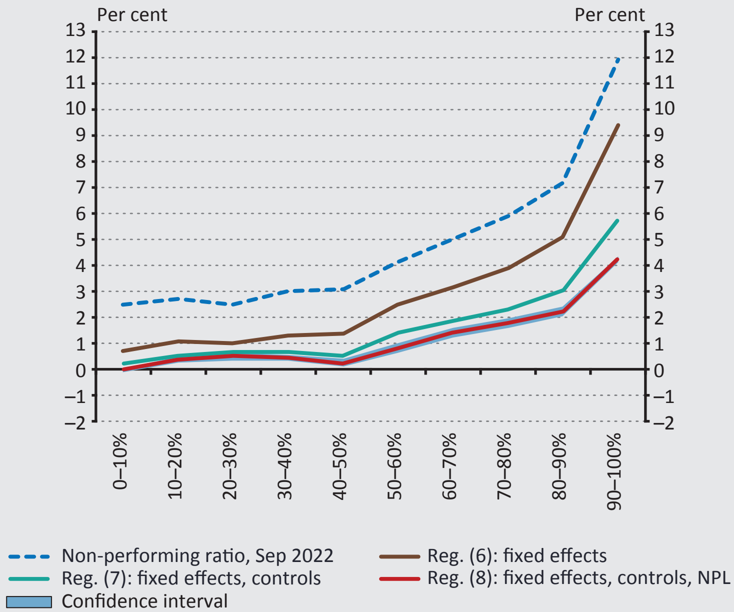
Table 2
Main results of the estimated linear probability models

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Non-performance in September 2022							
Moratorium type (reference: never in morat.)								
Dropped out at the end	0.0992***	0.0824***	0.0473***	0.0315***				
Voluntarily left	0.0141***	0.0072***	0.0031***	–0.0010***				
Moratorium intensity (reference: 0%)								
0–10%					0.0245***	0.0070***	0.0018***	–0.0004
10–20%					0.0273***	0.0107***	0.0050***	0.0032***
20–30%					0.0249***	0.0100***	0.0065***	0.0047***
30–40%					0.0302***	0.0131***	0.0065***	0.0042***
40–50%					0.0305***	0.0136***	0.0047***	0.0022***
50–60%					0.0414***	0.0244***	0.0138***	0.0080***
60–70%					0.0503***	0.0318***	0.0183***	0.0137***
70–80%					0.0586***	0.0390***	0.0226***	0.0175***
80–90%					0.0715***	0.0506***	0.0305***	0.0224***
90–100%					0.1190***	0.0941***	0.0569***	0.0420***
Sample size (thousand pcs)	2,384	2,384	2,384	2,384	2,384	2,384	2,384	2,384
R^2	0.064	0.068	0.169	0.321	0.068	0.068	0.170	0.322
Fixed effects: year of contr., bank, district, settlement type	N	Y	Y	Y	N	Y	Y	Y
Debtor and loan characteristics	N	N	Y	Y	N	N	Y	Y
Non-performance in October 2021	N	N	N	Y	N	N	N	Y

*Note: We use household loans existing in October 2021, exited the payment moratorium until the end of October 2021 permanently or never participated in it, and including observations for each of the variables in each model specification. The dependent variable in each specification is the September 2022 non-performing classification (non-performing: 1, performing: 0). The fixed effects, debtor and loan characteristics used as explanatory variables are detailed in Table 3 in the Appendix. The detailed estimation results are shown in Table 7 in the Appendix. Standard errors are clustered at the client level. *p<0.10, **p<0.05, *** p<0.01.*

Using moratorium intensity, the non-linear relationship is also apparent *(Figure 7).* In the broadest specification (8), the probability of non-performance in September 2022 for contracts with a moratorium intensity of up to 50 per cent is only at most one half a percentage point higher on average than for the group with moratorium intensity 0. Once the 50 per cent threshold is passed, the coefficients increase more and more, reaching 4.2 per cent for moratorium intensities close to 100 per cent. This value can explain about half of the difference in non-performing ratios between the groups that took almost full advantage of the general moratorium and that did not participate at all.

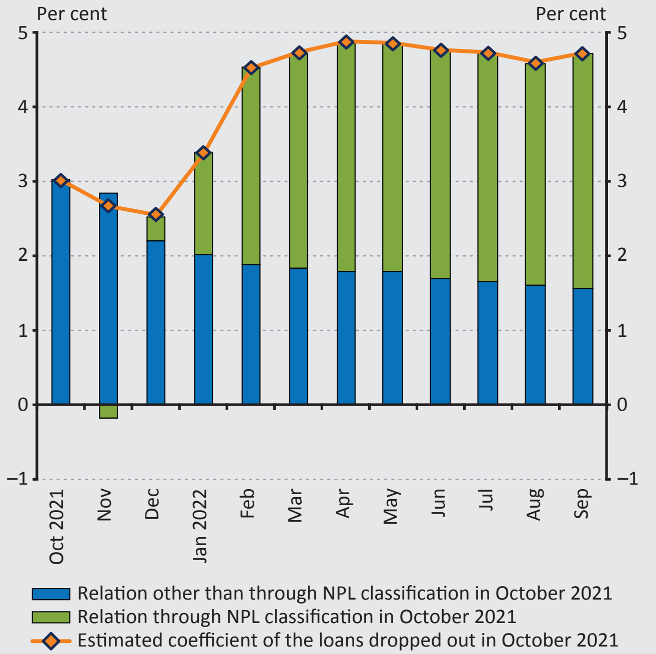
Figure 7
Estimated coefficients of moratorium intensity and the ratio of non-performing loans in September 2022



Note: The figure shows the estimated parameters of regressions (6) to (8) of Table 2 for each category of moratorium intensity (the reference group includes the loans with primary borrowers with moratorium intensity 0 per cent), and the share of the non-performing part within the outstanding debt in September 2022 of the loans that also existed in October 2021 and participated only in the general moratorium at most.

The inclusion of explanatory variables adds a lot of accuracy to the models' ability to identify subsequent non-performances. Regression (1), which uses only participation in the general moratorium as an explanatory variable, produces an AUROC value of 0.70, while the full specification (4) yields an AUROC value of 0.90. Non-performing classifications at the end of the general moratorium were included last in the analysis. A comparison of regressions (3) and (4), as well as (7) and (8), shows that the model's explanatory power improves significantly, but even this does not render the moratorium track record redundant. Based on *Figure 8*, we can add that the predictive power of end-of-programme non-performing classifications for subsequent non-performance steadily decreases over time, while the role of the moratorium track record does not weaken. This finding suggests that relevant information that could be acquired again after the programme has continuously overwritten the knowledge used to identify non-performing loans at the end of the moratorium. However, it seems that in this process, "intensive" participation in general moratorium does not count as information that quickly becomes obsolete.

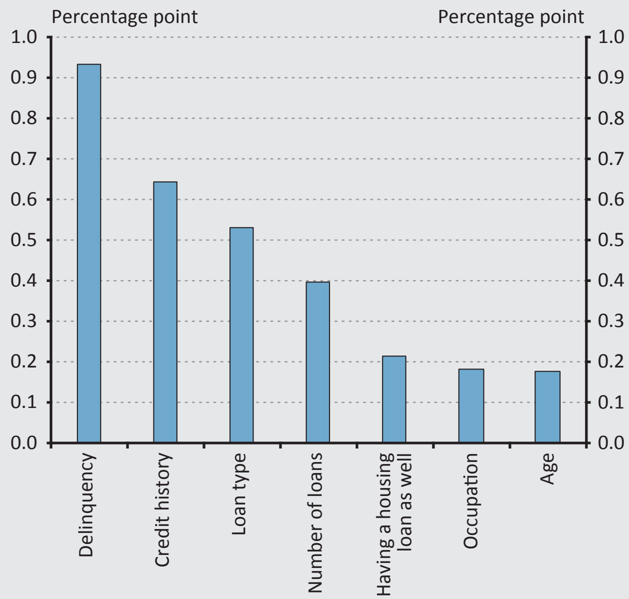
Figure 8
Estimated coefficients for the group of contracts exited at the end of the general moratorium



Note: The curve shows the estimated coefficients of the indicator variable for the group exited the general moratorium at the end of the programme in regression (3) of Table 2, using the values of the dependent variable in different months. The heights of the green columns correspond to the values of the same coefficient derived from the analogous estimates in regression (4).

For all other explanatory variables, it is generally true that their estimated coefficients are significant in all regressions (*Table 7* in the *Appendix*). Furthermore, some variables have significant predictive power. As shown in *Figure 9*, current delinquency, primary borrower's past delinquencies, differences in loan types and number of loans held by the primary borrower are the characteristics that most strongly decrease the estimated coefficient of the indicator variable for the loans left the general moratorium at its end. These variables are therefore most closely associated with intensive participation in the moratorium and subsequent credit risk.

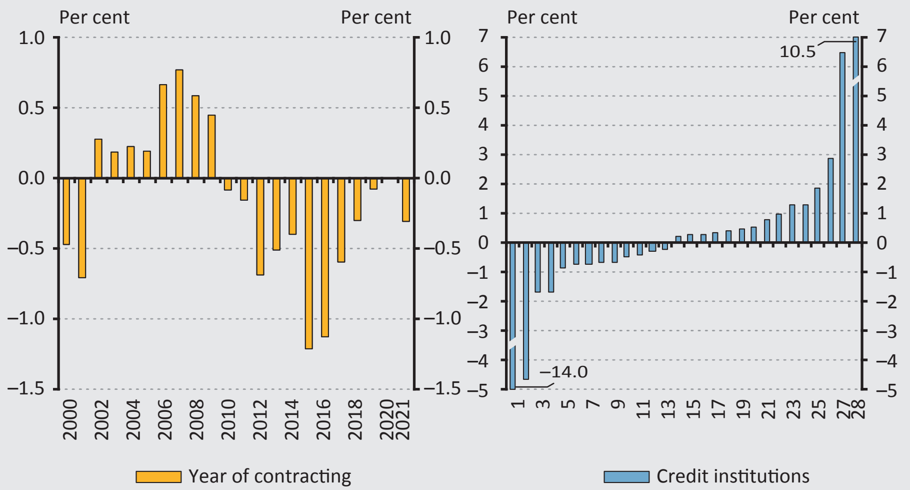
Figure 9
Impact of omitting certain explanatory variables on the estimated coefficient of participation in the moratorium



Note: Credit history: Whether the primary borrower has ever been delinquent on any previous loans. Having a housing loan as well: Whether the primary borrower also has a housing loan in addition to the particular loan. Occupation: First digit of the ISCO code of the primary borrower's occupation. The columns show the differences between the values of the coefficients of the indicator variable for the loans exiting the general moratorium at the end obtained by the two estimations of regression (3) in Table 2. The value obtained from the original estimate of regression (3) is subtracted from the estimated value obtained by omitting an explanatory variable from regression (3). The variables with the largest differences are shown in the figure.

According to the estimated coefficients of the fixed effects, which are often significantly different from one another, further unobserved but relevant region-, time- and bank-specific factors also play a role. Contracts signed between 2006 and 2009, the years of the financial cycle that accumulated excessive systemic risk, have higher additional probabilities of non-performance (*Figure 10, left panel*). Contracts concluded in 2015 and 2016 have particularly low values, partly, we think, due to the debt cap rules that came into force at the time.[16] The fixed effects of credit institutions also show significant variability, suggesting the presence of unobserved institution-specific factors in the credit supply that can be associated with credit risk (*Figure 10, right panel*).

Figure 10
Estimated fixed effects



Note: Based on estimation results of regression (4) in Table 2. The reference year is 2020 in the left panel. Individual institutions are anonymised. There are 32 credit institutions in the database, but only 28 in the smaller sample of the regression, because for some of the smaller institutions, due to the large number of explanatory variables used, there are no contracts for which values for all variables are available. Institutions are treated individually in the regressions, rather than consolidating those belonging to the same group of institutions.

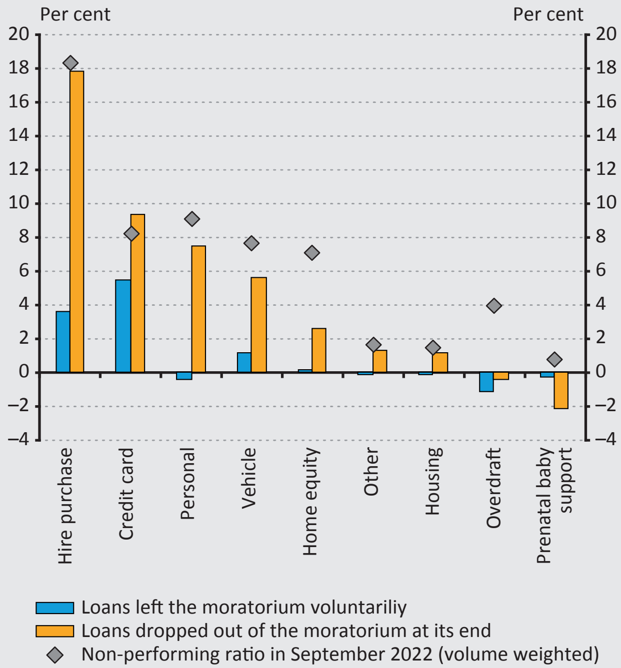
5. Robustness checks

Different loan types serve significantly different consumer needs, and therefore the interaction between the moratorium track record and loan type is also worth examining. Incorporating these into model (4), we get a significant heterogeneity according to loan types (*Figure 11*). For consumer loans, the average probability of subsequent non-performance is much higher for loans that left the programme at the end of the general moratorium, compared to the average for loans that

[16] In line with international developments, a comprehensive macroprudential toolkit was developed in Hungary in the 2010s to mitigate systemic financial risks. One particularly important step was the introduction of the so-called debt cap rules on 1 January 2015 to prevent the over-indebtedness of households (*Fáykiss et al. 2018*). These limit the loan amount that can be borrowed in proportion to the collateral and the monthly instalment that can be undertaken in proportion to income. The former is done by regulating the so-called loan-to-value ratio and the latter by regulating the so-called debt service-to-income ratio.

never participated in the moratorium. This additional probability is close to 18 percentage points for hire purchase loans, nearly 8 percentage points for personal loans and only 1 percentage point for housing loans. These values are considerable because their magnitudes are comparable to the respective non-performance ratios observed in September 2022.

Figure 11
Estimated coefficients of participation in the moratorium for each loan type



Note: The results were obtained from a version of model (4) in Table 2 including additional explanatory variables, which were the indicator variables for loan types multiplied by the indicator variables for the moratorium track record. The figure shows the estimated coefficients for the subgroups by loan type and moratorium track record, so that for each loan type, the reference group is composed of loans that did not participate in moratorium from that loan type.

If we also use the contract and debtor characteristics that significantly decrease the number of observations that can be used in the analysis, we obtain the results in *Table 4* and *5* in the *Appendix*. These variables characterise the income situation of the primary borrower at the beginning of the pandemic, between March and December 2020.[17] They also include the remaining maturity and the interest rate

[17] These variables are: (1) average monthly income before the pandemic, i.e. between March and December 2019, (2) annual change in income between March and December 2020 compared to the same period in 2019, (3) whether income decreased by at least 10 per cent during this period, (4) whether income was missing for at least 6 months between March and December 2020.

period of the loan and the net financial transfer that can be achieved by opting for the general moratorium.[18] These variables collectively reduce sample size from 2.38 million to 0.88 million. *Table 4* shows the estimates obtained with this smallest sample, and *Table 5* shows the estimates obtained with the largest samples that can be used for the respective model specifications. Models using as many explanatory variables as possible give estimates very similar to those of the baseline analysis.

The ratio of non-performing loans is generally very low, and therefore linear probability models may not properly capture the typically small, non-negative probabilities of non-performance. To potentially improve the alignment, regressions are also estimated using a logit model. According to the broadest models in *Table 6* of the *Appendix*, loans that left the general moratorium at its end, and within that, those that took full advantage of the programme, were on average 3.6 and 4.3 percentage points more likely to become non-performing than those that never participated in the programme. These are very similar to the values obtained in the baseline analysis (3.2 and 4.2 percentage points). However, logit models provide less support for the nonlinearity of the relationship between moratorium participation and subsequent non-performance. This is because there is a minor additional probability (0.3 percentage points) estimated for loans that voluntarily left the programme before its end, and the relationship between moratorium intensity and subsequent non-performance is closer to linear than in the baseline analysis.

6. Conclusion

We find a close and, according to the available information, non-linear relationship between participation in the general household loan repayment moratorium introduced in March 2020 to cushion the economic shocks of the coronavirus pandemic in Hungary and the debt servicing difficulties observed after the end of the programme in October 2021. The analysis using contract-level data shows that spending a short time in the moratorium and especially exiting voluntarily are associated with roughly the same subsequent probability of non-performance as no participation at all, while a long time in the moratorium and an involuntary exit at the end of the programme are associated with a significantly higher probability. By taking into account a number of characteristics for debtors, loans and credit institutions, we can conclude that the moratorium track record itself has significant predictive power for non-performance even in the 11th month after the general moratorium. We can explain almost half of the difference between the non-performing ratios in September 2022 among the loans that make the most and

[18] The difference between the net present values of the cash flows from the loan contract under the full utilisation of the general moratorium and under the full opt-out, calculated at a discount rate of 3 per cent, and expressed as a percentage of the outstanding debt in October 2021.

those that make the least use of the payment moratorium with the correlation shown.

Non-performing classifications by credit institutions at the end of the general moratorium are less and less predictive of non-performances more distant in time. By contrast, sustained participation in the general moratorium is a continuously strong predictor of subsequent non-performance. There are likely to exist additional explanatory variables not included in the analysis, that are difficult to observe, but are related to the loan repayment difficulties after the general moratorium. This is suggested by the fact that even in our most extensive model specifications, a number of fixed effects for years of contracting, districts and banks are significant.

There are several possible explanations for the link between the moratorium track record and subsequent non-performance. First, the fact that the debtors are more aware than others of the labour market, private life or health risks affecting their ability to repay their debts may play a role. Debtors worse off were more in need of the general moratorium, and if they stayed in the programme as long as possible, this may indicate that their ability to pay did not improve sufficiently. By contrast, those who left the programme voluntarily could assess that their situation had improved significantly. Second, the differences in preferences and bounded rationality between individuals, which are also difficult to observe, may also account for the correlation shown. The less one takes into account longer-term expenditures, the more likely one is to have both a worse ability to pay and due to necessity, a higher moratorium intensity. Third, the payment moratorium itself may cause a rise in the subsequent credit risk if it erodes the hardly observable efforts exerted by debtors to maintain or improve their solvency. Overall, therefore, it is not possible from our results to determine the extent to which the moratorium causes subsequent non-performance.

As seen, despite the correlation between the moratorium track record and subsequent payment difficulties, it was not the loans exited the general moratorium that mainly increased the share of non-performing loans after the end of the programme. Credit institutions classified slightly less than 3 per cent of household loans as non-performing at the end of the programme, a figure that rose to above 4 per cent after the programme. This change mainly related to loans remaining in conditional moratorium reserved for certain vulnerable groups of borrowers. Access to the conditional moratorium, unlike the general moratorium, was not automatic, so the initiation of entry could in itself indicate higher risks around the debtor's solvency, which could have played a significant role in classifying these loans as non-performing in an increased number.

Our results suggest that intensive participation in any systemic, voluntary, and temporary payment relief scheme may in itself be an important indicator of persistently higher credit risk of the loan after the programme. Any economic actor seeking to predict the probability of future default on a household loan based on observable circumstances should consider taking into account this characteristic of debtors. It could, for example, help commercial banks to make their loan loss provisioning practices more accurate and simultaneously more prudent. It can also improve the effectiveness of micro- and macroprudential policy by enhancing the accuracy of supervisory and system-wide stress tests and other risk monitoring models.

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Appendix

Table 3
Variables used for regression analysis

Name	Content	Type	Application
	Characteristics of the primary borrower		
Moratorium intensity	The 11 categories formed from moratorium intensity: (1) 0 per cent, (2) more than 0 per cent and at most 10 per cent, … (11) more than 90 per cent and at most 100 per cent.	cat.	basel. an.
Natural person	Can the primary borrower classified as a natural person?	cat.	basel. an.
Age	The age of the primary borrower measured in years.	disc.	basel. an.
ISCO_1	Occupation of the primary borrower according to the first digits of the ISCO codes.	cat.	basel. an.
Previous delinquency	Has the primary borrower ever been delinquent on any loan repayment?	cat.	basel. an.
ln(income 2019)	The logarithm of the average monthly income of the primary borrower between March and December 2019. The unit of measure of the income is HUF thousand.	cont.	rob. ch.
Large income decrease	Did the total income of the primary borrower between March and December 2020 decrease by at least 10 per cent compared to the same period of 2019?	cat.	rob. ch.
Income decrease	By what percentage did the total income of the primary borrower between March and December 2020 decrease compared to the same period of 2019?	cont.	rob. ch.
Job loss	Did the primary borrower have zero income for at least 6 months between March and December 2020?	cat.	rob. ch.
DSTI	Debt service-to-income ratio, expressed as a percentage. Its values are imputed before 2015 on the basis of all instalments of the debtor at the beginning of 2020 and the average monthly income in 2019.	cont.	basel. an.
Debt cap	Indicator for the existence of the debt cap rules in Hungary. It takes the value of 0 before 2015, and 1 from 2015.	cat.	basel. an.
No. of add. loans	Number of additional loans of the primary borrower, its highest value is 7.	cat.	basel. an.
Add. loan: housing	Does the primary borrower also have a housing loan in addition to the given loan?	cat.	basel. an.
Add. loan: personal	Does the primary borrower also have a personal loan in addition to the given loan?	cat.	basel. an.
Add. loan: vehicle	Does the primary borrower also have a vehicle loan in addition to the given loan?	cat.	basel. an.
Add. loan: hire purchase	Does the primary borrower also have a hire purchase loan in addition to the given loan?	cat.	basel. an.
Add. loan: overdraft	Does the primary borrower also have an overdraft in addition to the given loan?	cat.	basel. an.
Add. loan: credit card	Does the primary borrower also have a credit card loan in addition to the given loan?	cat.	basel. an.

Name	Content	Type	Application
	Characteristics of the loan contract		
NPL Sept-2022	Is the loan non-performing in September 2022?	cat.	basel. an.
Moratorium type	Participation of the loan in the general moratorium: left before the end of the programme, left at the end of the programme, did not participate in the programme	cat.	basel. an.
Morat. spells	Has the loan entered the general moratorium at least twice? (We only apply the products of this variable with the bank fixed effects.)	cat.	basel. an.
NPL Oct-2021	Is the loan non-performing in October 2021?	cat.	basel. an.
Previous FX loan	It takes the value of 1 if the loan was foreign currency denominated previously, 2 if the debtor ever had another foreign currency denominated loan, 3 if the loan was foreign currency denominated previously and the debtor had another foreign currency denominated loan, 0 otherwise.	cat.	basel. an.
Net transfer	Difference in net present values of cash flows regarding the loan contract from full participation and no participation in the general moratorium using a 3 per cent discount rate, as a percentage of the outstanding debt in October 2021.	cont.	rob. ch.
Remaining maturity	Remaining maturity in October 2021, unit of measure is month	disc.	rob. ch.
Loan type	Loan type: housing, home equity, prenatal baby support, personal, vehicle, hire purchase, overdraft, credit card, other	cat.	basel. an.
Delinquency	Delinquency in October 2021, unit of measure is day	disc.	basel. an.
No. of debtors	Number of debtors in the loan contract, its highest value is 11.	disc.	basel. an.
Int. rate period	Interest rate period, its values are the following. 1: below 12 months, 2: 12 months, 3: between 12 and 60 months, 4: 60 months, 5: between 60 and 120 months, 6: 120 months, 7: between 120 and 240 months, 8: 240 months, 9: above 240 months	cat.	rob. ch.
Debt	Outstanding debt in October 2021, unit of measure is HUF million	cont.	basel. an.
Interest rate	Applicable interest rate in October 2021, unit of measure is per cent	cont.	basel. an.
	Fixed effects		
Year of contr.	Year of contracting	disc.	basel. an.
Bank	Credit institution ID	cat.	basel. an.
District	District of the primary borrower's residence	cat.	basel. an.
Settlement type	Settlement type of the primary borrower's residence. There are 5 categories: communities, large communities, towns and districts in the capital, county seats and cities with county rights, other.	cat.	basel. an.

Note: Abbreviations: category: cat.; discrete: disc.; continuous: cont.; baseline analysis: basel. an.; robustness check: rob. ch. Category variables are discrete variables whose finite values are used to construct indicator variables with two possible values. The variable takes the value of 1 if the answer to the yes-or-no question in the column "Content" is "yes" and 0 if the answer is "no".

Table 4
Main results of extended linear probability models estimated on the same sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Non-performance in September 2022							
Moratorium type (reference: never in morat.)								
Dropped out at the end	0.0787***	0.0686***	0.0386***	0.0233***				
Voluntarily left	–0.0060***	0.0014***	–0.0019***	–0.0068***				
Moratorium intensity (reference: 0%)								
0–10%					0.0190***	0.0052***	0.0010	–0.0018***
10–20%					0.0221***	0.0083***	0.0042***	0.0010
20–30%					0.0185***	0.0058***	0.0048***	0.0013*
30–40%					0.0236***	0.0109***	0.0068***	0.0018**
40–50%					0.0302***	0.0144***	0.0080***	0.0038***
50–60%					0.0370***	0.0203***	0.0122***	0.0041***
60–70%					0.0452***	0.0271***	0.0167***	0.0113***
70–80%					0.0514***	0.0318***	0.0194***	0.0136***
80–90%					0.0619***	0.0399***	0.0239***	0.0163***
90–100%					0.1020***	0.0762***	0.0438***	0.0301***
Sample size (thousand pcs)	876	876	876	876	876	876	876	876
R^2	0.037	0.109	0.180	0.298	0.063	0.107	0.179	0.298
Fixed effects: year of contr., bank, district, settlement type	N	Y	Y	Y	N	Y	Y	Y
Debtor and loan characteristics	N	N	Y	Y	N	N	Y	Y
Non-performance in October 2021	N	N	N	Y	N	N	N	Y

*Note: We use household loans existing in October 2021, exited the payment moratorium until the end of October 2021 permanently or never participated in it, and including observations for each of the variables in each model specification. The dependent variable in each specification is the September 2022 non-performing classification (non-performing: 1, performing: 0). In addition to the debtor and loan characteristics used in Table 2, we include also the following: (1) average monthly income before the pandemic, i.e. between March and December 2019, (2) annual change in income between March and December 2020 compared to the same period in 2019, (3) whether income decreased by at least 10 per cent during this period, (4) whether income was missing for at least 6 months between March and December 2020, (5) the remaining maturity of the loan, (6) the length of the interest rate period, (7) the amount of the net financial transfer that can be achieved by participating in the general moratorium. Standard errors are clustered at the client level. *p<0.10, **p<0.05, *** p<0.01.*

Table 5
Main results of extended linear probability models estimated on the largest possible samples

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Non-performance in September 2022							
Moratorium type (reference: never in morat.)								
Dropped out at the end	0.0660***	0.0590***	0.0386***	0.0233***				
Voluntarily left	–0.0054***	–0.0021***	–0.0019***	–0.0068***				
Moratorium intensity (reference: 0%)								
0–10%					0.0059***	0.0027***	0.0010	–0.0018***
10–20%					0.0109***	0.0083***	0.0042***	0.0010
20–30%					0.0085***	0.0059***	0.0048***	0.0013*
30–40%					0.0122***	0.0078***	0.0068***	0.0018**
40–50%					0.0136***	0.0079***	0.0080***	0.0038***
50–60%					0.0232***	0.0175***	0.0122***	0.0041***
60–70%					0.0309***	0.0248***	0.0167***	0.0113***
70–80%					0.0397***	0.0320***	0.0194***	0.0136***
80–90%					0.0529***	0.0444***	0.0239***	0.0163***
90–100%					0.0854***	0.0730***	0.0438***	0.0301***
Sample size (thousand pcs)	4,456	4,456	876	876	4,456	4,456	876	876
R^2	0.022	0.056	0.180	0.298	0.024	0.058	0.179	0.298
Fixed effects: year of contr., bank, district, settlement type	N	Y	Y	Y	N	Y	Y	Y
Debtor and loan characteristics	N	N	Y	Y	N	N	Y	Y
Non-performance in October 2021	N	N	N	Y	N	N	N	Y

*Note: We use household loans existing in October 2021 exited the payment moratorium until the end of October 2021 permanently or never participated in it. The dependent variable in each specification is the September 2022 non-performing classification (non-performing: 1, performing: 0). We always use the largest sample available for a given model. In addition to the debtor and loan characteristics used in Table 2, we include also the following: (1) average monthly income before the pandemic, i.e. between March and December 2019, (2) annual change in income between March and December 2020 compared to the same period in 2019, (3) whether income decreased by at least 10 per cent during this period, (4) whether income was missing for at least 6 months between March and December 2020, (5) the remaining maturity of the loan, (6) the length of the interest rate period, (7) the amount of the net financial transfer that can be achieved by participating in the general moratorium. Standard errors are clustered at the client level. *p<0.10, **p<0.05, *** p<0.01.*

Table 6
Main results of the estimated logit models

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Non-performance in September 2022				
Moratorium type (reference: never in morat.)								
Dropped out at the end	0.0760***	0.0751***	0.0446***	0.0362***				
Voluntarily left	–0.0092***	–0.0020***	0.0025***	0.0029***				
Moratorium intensity (reference: 0%)								
0–10%					0.0049***	0.0063***	0.0041***	0.0046***
10–20%					0.0077***	0.0098***	0.0092***	0.0101***
20–30%					0.0053***	0.0083***	0.0100***	0.0106***
30–40%					0.0106***	0.0126***	0.0125***	0.0130***
40–50%					0.0109***	0.0130***	0.0117***	0.0121***
50–60%					0.0219***	0.0244***	0.0209***	0.0202***
60–70%					0.0307***	0.0319***	0.0251***	0.0234***
70–80%					0.0390***	0.0385***	0.0290***	0.0263***
80–90%					0.0519***	0.0492***	0.0343***	0.0295***
90–100%					0.0996***	0.0864***	0.0507***	0.0428***
Sample size (thousand pcs)	2,384	2,381	2,381	2,381	2,384	2,381	2,381	2,381
Fixed effects: year of contr., bank, district, settlement type	N	Y	Y	Y	N	Y	Y	Y
Debtor and loan characteristics	N	N	Y	Y	N	N	Y	Y
Non-performance in October 2021	N	N	N	Y	N	N	N	Y

*Note: We use household loans existing in October 2021 exited the payment moratorium until the end of October 2021 permanently or never participated in it, and including observations for each of the variables in each model specification. The dependent variable in each specification is the September 2022 non-performing classification (non-performing: 1, performing: 0). The explanatory variables are the same as those used in the baseline analysis (see Table 3). Standard errors are clustered at the client level. *p<0.10, **p<0.05, *** p<0.01.*

Table 7
Detailed results of the estimated linear probability models

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Non-performance in September 2022							
Moratorium type (reference: never in moratorium)								
Dropped out at the end	0.0992***	0.0824***	0.0473***	0.0315***				
	(0.0004)	(0.0005)	(0.0005)	(0.0004)				
Voluntarily left	0.0141***	0.0072***	0.0031***	–0.0010***				
	(0.0002)	(0.0003)	(0.0003)	(0.0003)				
Moratorium intensity (reference: 0%)								
0–10%					0.0245***	0.0070***	0.0018***	–0.0004
					(0.0005)	(0.0006)	(0.0005)	(0.0005)
10–20%					0.0273***	0.0107***	0.0050***	0.0032***
					(0.0006)	(0.0006)	(0.0006)	(0.0006)
20–30%					0.0249***	0.0100***	0.0065***	0.0047***
					(0.0006)	(0.0007)	(0.0006)	(0.0006)
30–40%					0.0302***	0.0131***	0.0065***	0.0042***
					(0.0007)	(0.0008)	(0.0008)	(0.0007)
40–50%					0.0305***	0.0136***	0.0047***	0.0022***
					(0.0007)	(0.0008)	(0.0008)	(0.0007)
50–60%					0.0414***	0.0244***	0.0138***	0.0080***
					(0.0009)	(0.0009)	(0.0009)	(0.0008)
60–70%					0.0503***	0.0318***	0.0183***	0.0137***
					(0.0010)	(0.0010)	(0.0010)	(0.0009)
70–80%					0.0586***	0.0390***	0.0226***	0.0175***
					(0.0010)	(0.0010)	(0.0010)	(0.0009)
80–90%					0.0715***	0.0506***	0.0305***	0.0224***
					(0.0010)	(0.0010)	(0.0010)	(0.0009)
90–100%					0.1190***	0.0941***	0.0569***	0.0420***
					(0.0006)	(0.0006)	(0.0006)	(0.0005)
NPL Oct-2021				0.5230***				0.5230***
				(0.0020)				(0.0020)

Table 7
Detailed results of the estimated linear probability models

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Non-performance in September 2022				
ISCO_1								
1			–0.0025***	–0.0019***			–0.0030***	–0.0022***
			(0.0006)	(0.0005)			(0.0006)	(0.0005)
2			–0.0074***	–0.0059***			–0.0077***	–0.0059***
			(0.0004)	(0.0004)			(0.0004)	(0.0004)
3			–0.0083***	–0.0068***			–0.0085***	–0.0069***
			(0.0005)	(0.0004)			(0.0005)	(0.0004)
4			–0.0078***	–0.0071***			–0.0081***	–0.0072***
			(0.0008)	(0.0007)			(0.0008)	(0.0007)
5			–0.0035***	–0.0030***			–0.0040***	–0.0033***
			(0.0006)	(0.0006)			(0.0006)	(0.0006)
6			0.0044	0.0064**			0.0038	0.0059**
			(0.0030)	(0.0028)			(0.0030)	(0.0028)
7			–0.0035***	–0.0023***			–0.0042***	–0.0029***
			(0.0006)	(0.0006)			(0.0006)	(0.0006)
8			–0.0012**	–0.0006			–0.0018***	–0.0010*
			(0.0006)	(0.0005)			(0.0006)	(0.0005)
9			0.0236***	0.0197***			0.0229***	0.0192***
			(0.0008)	(0.0008)			(0.0008)	(0.0008)
Natural person			0.0008	–0.0574***			0.0075	–0.0529***
			(0.0053)	(0.0053)			(0.0053)	(0.0053)
Previous FX loan								
1			–0.0167***	–0.0123***			–0.0173***	–0.0127***
			(0.0003)	(0.0003)			(0.0003)	(0.0003)
2			0.0375	0.0253			0.0374	0.0255
			(0.0380)	(0.0175)			(0.0375)	(0.0170)
3			0.0054*	–0.0043**			0.0035	–0.0055***
			(0.0028)	(0.0020)			(0.0028)	(0.0020)
Previous delinquency			0.0811***	0.0500***			0.0812***	0.0499***
			(0.0007)	(0.0006)			(0.0007)	(0.0006)

Table 7
Detailed results of the estimated linear probability models

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
			Non-performance in September 2022					
Delinquency								
31–60 days			0.2070***	0.2010***			0.2060***	0.2010***
			(0.0065)	(0.0065)			(0.0065)	(0.0065)
61–90 days			0.2310***	0.2110***			0.2310***	0.2120***
			(0.0089)	(0.0087)			(0.0089)	(0.0087)
91–180 days			0.2610***	0.0986***			0.2610***	0.0990***
			(0.0065)	(0.0062)			(0.0065)	(0.0062)
181–360 days			0.2690***	0.0982***			0.2700***	0.0987***
			(0.0053)	(0.0046)			(0.0053)	(0.0046)
361 days or more			0.2830***	0.1220***			0.2840***	0.1220***
			(0.0022)	(0.0020)			(0.0022)	(0.0020)
DSTI			0.0142***	0.0049***			0.0138***	0.0045***
			(0.0005)	(0.0004)			(0.0005)	(0.0004)
Debt cap * DSTI			0.0037***	0.0254***			0.0011	0.0232***
			(0.0011)	(0.0010)			(0.0011)	(0.0010)
No. of debtors								
2			0.0009**	–0.0008**			0.0003	–0.0012***
			(0.0004)	(0.0003)			(0.0004)	(0.0003)
3			–0.0010	–0.0006			–0.0023***	–0.0016***
			(0.0007)	(0.0006)			(0.0007)	(0.0006)
4			–0.0027**	–0.0014			–0.0041***	–0.0025**
			(0.0014)	(0.0011)			(0.0014)	(0.0011)
5			0.0039	0.0020			0.0016	0.0002
			(0.0047)	(0.0035)			(0.0047)	(0.0035)
6			–0.0006	–0.0043			0.0003	–0.0037
			(0.0085)	(0.0051)			(0.0085)	(0.0051)
7			–0.0035	–0.0062			0.0008	–0.0030
			(0.0261)	(0.0128)			(0.0261)	(0.0128)
8			–0.0426**	–0.0291***			–0.0436**	–0.0301**
			(0.0182)	(0.0109)			(0.0215)	(0.0132)
9			–0.1270***	–0.0796***			–0.1330***	–0.0860***
			(0.0043)	(0.0040)			(0.0043)	(0.0041)
10			–0.0314	–0.0176			–0.0413	–0.0241
			(0.0526)	(0.0383)			(0.0597)	(0.0440)
11			–0.0355***	–0.0140***			–0.0365***	–0.0127***
			(0.0016)	(0.0013)			(0.0016)	(0.0013)

Table 7
Detailed results of the estimated linear probability models

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
			Non-performance in September 2022					
Age			–0.0007***	–0.0005***			–0.0007***	–0.0005***
			(0.0000)	(0.0000)			(0.0000)	(0.0000)
Debt			–0.00007***	–0.0002***			–0.00004**	–0.0002***
			(0.00002)	(0.00002)			(0.00002)	(0.00002)
Loan type								
home equity			0.0051***	0.0033***			0.0059***	0.0036***
			(0.0006)	(0.0005)			(0.0006)	(0.0005)
prenatal baby support			0.0051***	0.0014***			0.0064***	0.0024***
			(0.0005)	(0.0004)			(0.0005)	(0.0004)
personal			0.0258***	0.0192***			0.0247***	0.0179***
			(0.0006)	(0.0005)			(0.0006)	(0.0005)
vehicle			–0.0149***	–0.0192***			–0.0147***	–0.0189***
			(0.0012)	(0.0011)			(0.0012)	(0.0011)
hire purchase			0.0353***	0.0395***			0.0355***	0.0391***
			(0.0013)	(0.0012)			(0.0013)	(0.0012)
overdraft			0.0033***	0.0077***			0.0088***	0.0115***
			(0.0007)	(0.0007)			(0.0007)	(0.0007)
credit card			–0.0213***	–0.0057***			–0.0193***	–0.0038***
			(0.0010)	(0.0009)			(0.0010)	(0.0009)
other			–0.0122***	0.0033			–0.0031	0.0093**
			(0.0045)	(0.0040)			(0.0045)	(0.0040)
Interest rate			0.0341***	0.0223***			0.0322***	0.0203***
			(0.0029)	(0.0027)			(0.0029)	(0.0027)
Add. loan:								
housing			–0.0241***	–0.0156***			–0.0280***	–0.0180***
			(0.0005)	(0.0005)			(0.0005)	(0.0005)
personal			–0.0102***	–0.0021***			–0.0156***	–0.0059***
			(0.0005)	(0.0005)			(0.0005)	(0.0005)
vehicle			–0.0235***	–0.0137***			–0.0246***	–0.0142***
			(0.0011)	(0.0010)			(0.0011)	(0.0010)
hire purchase			–0.0310***	–0.0139***			–0.0308***	–0.0136***
			(0.0007)	(0.0007)			(0.0007)	(0.0007)
overdraft			–0.0069***	0.0006			–0.0087***	–0.0006
			(0.0006)	(0.0005)			(0.0006)	(0.0006)
credit card			–0.0096***	–0.0041***			–0.0096***	–0.0037***
			(0.0005)	(0.0005)			(0.0005)	(0.0005)

Table 7
Detailed results of the estimated linear probability models

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Non-performance in September 2022				
No. of add. loans								
1			0.0621***	0.0374***			0.0653***	0.0390***
			(0.0007)	(0.0005)			(0.0007)	(0.0005)
2			0.0780***	0.0465***			0.0823***	0.0488***
			(0.0009)	(0.0007)			(0.0009)	(0.0007)
3			0.0953***	0.0560***			0.1030***	0.0604***
			(0.0012)	(0.0010)			(0.0012)	(0.0010)
4			0.1110***	0.0639***			0.1210***	0.0703***
			(0.0017)	(0.0015)			(0.0017)	(0.0015)
5			0.1250***	0.0710***			0.1380***	0.0791***
			(0.0029)	(0.0027)			(0.0030)	(0.0027)
6			0.1450***	0.0810***			0.1570***	0.0890***
			(0.0100)	(0.0096)			(0.0099)	(0.0095)
7			0.1980***	0.1280***			0.2130***	0.1370***
			(0.0340)	(0.0340)			(0.0341)	(0.0341)
Settlement type								
county seats		–0.0077***	0.0008	0.0005		–0.0076***	0.0007	0.0006
		(0.0006)	(0.0006)	(0.0005)		(0.0006)	(0.0006)	(0.0005)
large communities		0.0000	0.0017**	0.0016**		–0.0001	0.0017**	0.0016**
		(0.0009)	(0.0008)	(0.0007)		(0.0009)	(0.0008)	(0.0007)
towns		–0.0066***	–0.0014***	–0.0014***		–0.0066***	–0.0014***	–0.0014***
		(0.0005)	(0.0004)	(0.0004)		(0.0005)	(0.0004)	(0.0004)
other		–0.0004	–0.0051	–0.0032		0.0001	–0.0046	–0.0028
		(0.0042)	(0.0040)	(0.0039)		(0.0042)	(0.0040)	(0.0039)
Sample size (thousand pcs)	2,384	2,384	2,384	2,384	2,384	2,384	2,384	2,384
R^2	0.064	0.068	0.169	0.321	0.068	0.068	0.170	0.322
Fixed effects: year of contr., bank, district, settlement type	N	Y	Y	Y	N	Y	Y	Y
Debtor and loan characteristics	N	N	Y	Y	N	N	Y	Y
Non-performance in October 2021	N	N	N	Y	N	N	N	Y

*Note: Details of the results in Table 2. Standard errors in parentheses are clustered at the client level. *p<0.10, **p<0.05, *** p<0.01.*