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The Effect of Personal Credit Card Limits on Card Use: Micro Data Evidence from An Emerging Market

By *Mehmet Selman Çolak, Yavuz Kılıç, Yusuf Yıldırım, and Muhammed Hasan Yılmaz*

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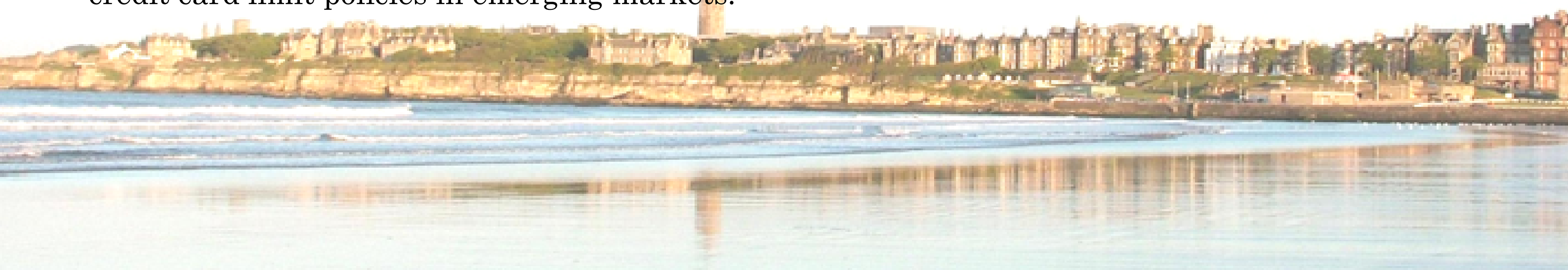

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Mehmet Selman Çolak[*] Yavuz Kılıç[†] Yusuf Yıldırım[‡] Muhammed Hasan Yılmaz[§]

Abstract

This study investigates the impact of personal credit card (PCC) limit increases on households' credit card spending patterns. Using proprietary data of individual borrowers from the Credit Registry of Türkiye for the period 2015-2024, we investigate how credit card balances respond to widespread and sizeable limit hikes after 2022, amidst rising inflation and amplified domestic consumption. Using a difference-in-differences (DiD) methodology, we identify a treatment group with limit increases greater than the cumulative inflation rate in the post-2022 period and a control group with limit increases that are consistent with macroeconomic dynamics. Our findings highlight a significant divergence in spending patterns following the upward revisions in card limits, which results in elevating card spending balances, particularly pronounced in higher limit brackets. Additional robustness checks including placebo tests, alternative ways to measure card spending, extensions to account for potential confounding factors and alternative treatment group definitions all corroborate our baseline results. Our work aims to contribute to the prior literature on how household spending responds to credit limit changes and the optimal credit limit strategy from lenders' and policymakers' perspectives, emphasizing the broader economic implications of credit card limit policies in emerging markets.

Keywords: Financial Stability, Credit Card Limits, Household Spending

JEL Classifications: C21, E21, E51

[*] Manager, Macro Financial Analysis Division, Central Bank of the Republic of Türkiye, selman.colak@tcmb.gov.tr
[†] Economist, Macro Financial Analysis Division, Central Bank of the Republic of Türkiye, yavuz.kilic@tcmb.gov.tr
[‡] Expert, Financial Stability Division, Central Bank of the Republic of Türkiye, yildirim.yusuf@tcmb.gov.tr
[§] Economist, Macro Financial Analysis Division, Central Bank of the Republic of Türkiye, muhammed.yilmaz@tcmb.gov.tr
Honorary Academic Fellow, Centre for Responsible Banking & Finance, University of St Andrews, mhy1@st-andrews.ac.uk

The views expressed in this paper are those of authors and do not reflect the official views of the Central Bank of the Republic of Türkiye. All the remaining errors are our own.

1. Introduction and Related Literature

Credit cards serve an important function in the context of modern financial systems, acting both as a simple payment mechanism and an essential instrument for household liquidity management. With the availability of card payments, the need to carry cash is reduced for individuals, and at the same time, the existence of such financial products allows the recording of economic transactions and activities. More importantly, by using credit cards, consumers have the opportunity to purchase goods and services in advance and pay at a later date, which is a leading indicator for the course of domestic demand and commercial activities. The offering of cash advances and installments with credit cards is another reason why consumers prefer to use such offerings, especially in emerging markets where budget planning has a paramount importance.

[Insert Charts 1 and 2 Here]

In the context of this paper, despite the fact that household indebtedness in Türkiye stays below the average of peer countries, credit cards are widely used and their share in household financial liabilities has been increasing in recent years (Chart 1 and Chart 2). Therefore, policymakers and financial institutions should be able to grasp the consequential impact of card limit changes on consumer spending in order to formulate and implement timely macroprudential measures in this credit segment.[1] In addition to its importance in terms of financial stability, credit card use serves as an early warning indicator concerning the course of macroeconomic indicators such as current account balance and price stability.

From a macroeconomic perspective, the relationship among credit card expenditures, inflation and current account balance is one of the most frequently studied topics in macro-financial literature. Although it is considered that credit card expenditures and inflation feed each other, there is widespread evidence on the potential mechanisms by which credit card expenditures increase inflation in emerging market cases (Geanakoplos and Dubey, 2010; Öğünç and Sarıkaya, 2015; Wong and Tang, 2020). Credit

[1] Currently, a number of macroprudential policies are implemented to ensure the healthy functioning of the credit card market in Türkiye. Individuals are encouraged to pay their card debts regularly, with the minimum payment rate varying according to limit groups. The application of a maximum limit indexed to income, is aimed at ensuring that card limits are compatible with income. The use of credit cards as a means of payment is encouraged by setting installment limitations and contractual (late payment) interest rates above other loan interest rates. The risk weight applied to credit card balances ensures that banks act cautiously in the card market.

card use may also negatively affect the current account balance through consumption and (intermediate goods) import channels, while influencing inflation through the channel of "advanced consumption" demand. As a result, determining credit card limits and payment conditions in line with income and inflation is of critical importance in terms of current account balance, price stability, and financial stability. In this paper, we exploit the recent developments in Türkiye (as a country facing sizeable inflation shocks in recent years) characterized by credit card limit increases with unprecedented magnitudes to test the impact of limit changes on household spending behavior.

To test the relationship between card limits and spending patterns, we collect micro-level data on card balances of a randomly selected sample of individual borrowers from the Credit Registry database available in the Central Bank of the Republic of Türkiye (CBRT). Our sample period spans the interval between 2015 and 2024. In this context, we exploit the sizeable limit increases observed for certain borrowers in the post-2022 era characterized by rising domestic consumption and unprecedented inflation shocks in a DiD setting. Specifically, we detect individuals in our sample having experienced a limit increase more than realized cumulative inflation aftermath of 2022 to form our treatment group, whereas other individuals are considered as a control group.

By way of preview, our descriptive analysis shows that average tendencies of card spending have followed indistinguishable patterns in treatment and control groups, only diverging following widespread limit increases. Our formal regression estimations also support this finding for a myriad of proxies monitoring card spending including nominal and real balances as well as the natural logarithm and growth rate transformations. Additionally, our disaggregated analyses examining the same effect across different limit brackets validate the positive effect on spending, albeit with stronger effects in high-bracket categories. Our findings remain similar against a set of robustness checks such as placebo tests, inclusion of other control variables, and alternative ways to define treatment group (i.e. median values of limit increase rather than recorded inflation). Our extended estimations further show that the sizeable shifts in card limits also result in larger card installment balances.

Our work attempts to contribute to two main parts of the prior literature. First, a strand of literature evaluates the effect of credit card limit increases on household spending. Aydın (2022) investigates the magnitude, heterogeneity, composition, and dynamics of the consumption response to an expansion of credit limit by employing a randomized controlled experimental design. It is found that the participants near their limits borrow and spend when limits are relaxed but put off spending and save out of constraints under the counterfactual when limits are tight. Soman and Cheema (2002) explore the effect of credit limits on spending decisions depending on credibility by using a variety of approaches including qualitative (surveys) and quantitative (multivariate regression) methods. According to their findings, consumers use the credit limits as a signal of future potential earnings, and hence the credit limit would positively impact their spending, particularly when the credibility of the limit is high. Gross and Souleles (2000) utilize a panel of individual credit card accounts from several different card issuers to analyze how people respond to changes in limits. They highlight that increases in credit limits generate an immediate and significant rise in debt, while the response is most visible among the people being closer to their limits. In turn, this provides evidence that liquidity constraints are binding.

Along similar lines, Bach et al. (2014) utilize a system dynamics approach to analyze the intricate association between credit card spending limits individuals' financial decisions over time. The experiments within their model demonstrate that the higher the credit limit approved on the credit card, the lower the budget available for spending in the long run. Grodzicki and Koulayev (2021) examine the dynamics of credit card borrowing and repayment in the US together with the expected costs of credit debt to consumers by revealing three important results: credit cards are predominantly used to borrow; card indebtedness is sustained for long periods while the balances frequently rise before being repaid; and the expected annualized cost of an episode of continuous borrowing is 28% of its initial balance, which is higher than the average annual percentage rate. Our paper contributes to this strand of literature by examining the effect of changes in credit limits on household spending choices in an emerging market (Türkiye) by employing a quasi-experimental design by exploiting the recent limit increases beyond the level implied by macroeconomic dynamics.

Second, another strand of the literature delves into the lender perspective and focuses on determining the optimal credit limit by minimizing asset quality risks and maximizing profitability for financial institutions. Trench et al. (2003) develop a method for managing the characteristics of a bank's cardholder portfolio optimally. Their proposed design involves the portfolio control and optimization (PORTICO) system using the Markov decision process (MDP) to select price points and credit lines for each cardholder that maximize net present value (NPV) for the portfolio. Miao et al. (2020) suggest a data-driven approach based on causal inference to manage the credit limit in a sophisticated way. Paul and Biswas (2017) aim to assign credit limits to new customers using Bayesian decision theory and fuzzy logic. Dey (2010) discusses the possibility of using simulation along with action-effect models to set the optimum credit limit for each account. Licari et al. (2021) use UK credit card data by applying the MDP model for credit card profitability to find the optimal dynamic credit limit policy. They treat both the behavioral score and the balance as state variables and employ the bucketing algorithm to identify the bands for the state variables with different risks.

Similarly, Sohn et al. (2014) implement regression models to determine the probability of customer default and the customer's current balance as a function of the credit line by developing a regression tree to identify groups of customers assigned the same credit line and employ the results to maximize overall net profit by adjusting individual credit limits. Budd and Taylor (2015) present a model to derive profitability from a credit card assuming that the cardholder pays the full outstanding balance. Our work extends this line of literature by demonstrating the distorting externalities of financial intermediaries' card limit decisions on household spending behavior by using an emerging market case defined by the high importance of credit cards in-household financing.

In addition to addressing these lines of prior academic literature, the study has another aspect that makes it special for policymakers. The extremely rapid increase observed in credit card limits in the recent period is rather a new phenomenon in Türkiye. To exemplify, a similar development was not observed in the preeceding inflationary period (albeit with the lower level of inflation shock) experienced in 2018. This situation constitutes an important source of motivation for studying credit card developments on a micro-scale. Additionally, since card limit and installment restrictions are used as macroprudential tools for the case of Türkiye, this issue is also important for policymakers.

The rest of the paper is structured as follows. Section 2 introduces the regulatory dataset and empirical design used for this study. Section 3 provides the empirical findings by conveying how average spending behavior evolves between households with and without limit increases beyond the shift in macroeconomic outlook. This section also gives DiD estimation results signifying the causal effect of limits on card spending in a formal manner together with additional analyses including placebo tests, the heterogeneity of main effects concerning limit brackets, and other robustness tests. Section 4 gives the concluding discussion.

2. Data and Methodology

For empirical analysis, we first gather detailed credit card information of a random sample of individuals, from the Credit Registry database available in CBRT for the period 2015-2024, which successfully represents population characteristics.[2] The random determination of the sample is considered as a factor that reduces the distorting effect of factors such as economic activity and spending behavior on the findings. In particular, this sample includes 655,750 individual-year observations (t = 10, n = 65,575) for borrowers with a limit of 50 thousand TL and above as of January 2024.[3] While people with non-missing card debt balances are considered for each period, inter-individual heterogeneities are controlled by keeping the same borrowers in the sample over the course of estimation period. Moreover, the limit groups in the study are determined according to the individuals' limit amounts in January 2024, and the limit and balance developments of the individuals in the groups over the last 10 years are analyzed by adjusting for the effect of inflation. The limits and the balance of the individuals were realized using the historical inflation rate.

[2] By randomly selecting the sample, it was aimed that the demographic characteristics of the sample (place of residence, age, gender, marital status, etc.) represent the total population. In addition, thanks to the random selection, inferences can be made regarding the credit card market in general, based on the findings obtained in the analysis. The lack of a data source matching income to credit limits restricts the ability to directly address self-selection bias. Two main steps have already been taken in the paper to reduce these potential biases:
1) Robustness Checks: Robustness checks were conducted using various model specifications and alternative control variables to ensure the validity of the findings.
2) Fixed Effects: A procedure was followed to control for fixed effects in model estimates to control for unobserved heterogeneity of individuals and to account for time-invariant characteristics.

[3] To minimize observation loss when manually extracting data from the data source, the lower limit level, which was determined as 50 thousand TL for 2024, was reduced by the CPI for previous years (for example, 30.3 thousand TL for 2023, 19.2 thousand TL for 2022, etc.).

Our empirical design is reminiscent of a DiD framework. Specifically, we compare the credit card use of individuals in our treatment group, for which the credit card limits had been updated (from January 2022 to January 2024) with a growth rate above the realized inflation rate (160% in that period), with a control group of individuals who had experienced a limit growth incompatible with the shift in economic fundamentals (below the realized inflation rate). This process yields 58,753 unique borrowers in the treated group contrasted with 6,822 unique credit card users in the control group. Our main specification is formulated as follows:

$$PCC\ Balance_{it} = \alpha + \beta(Post_t\ x\ High\ Limit_i) + \delta_i + \theta_t + \varepsilon_{it} \qquad (1)$$

where $PCC\ Balance$ stands for several proxies displaying the credit card usage tendency of user i at year t. In our empirical investigation, we make use of different indicators capturing this behavior including the natural logarithm of the card balance itself (ln_PCC) and the annual growth rate of the card balance (PCC_gr). The binary variable $Post$ signifies the post-2022 period before which we observe a visible divergence in banks' supply decisions concerning the credit card segment by adjusting the limits of individuals in a heterogenous way in response to inflationary shocks while taking the value of zero for the pre-2022 period. As explained above, the binary variable $High\ Limit$ takes the value of one for the credit card users benefiting from a limit increase above the macroeconomic fundamentals (in other words, above the inflation rate incurred from 2022 to 2024), otherwise zero. The main coefficient of the interest, β, is attached to the DiD term gauging the impact of excessive changes in card limits on spending behavior. We augment the model with conventional fixed effects including credit card user fixed effects (represented by δ_i) and year fixed effects (represented by θ_t). Our inferences are based on standard errors clustered at the credit card user level.

3. Empirical Findings

In the first step of our analysis, we visually examine the validity of parallel trend assumption by depicting the card balance and limit patterns of borrowers categorized in the treated and control groups. In this context, we use a variety of indicators for credit card balances and limits to reveal that, indeed, there was a parallel trend in the pre-2022 period, and this trend clearly left room for a visible divergence in the post-2022 period. As seen in

Chart 3, the real credit card balances of the control and treatment groups are separated following 2022. While the control group continued to decline in line with the pre-2022 trend, the treatment group reached its peak level in the post-2022.

[Insert Chart 3 Here]

When the development in the limits of the control and treatment groups is examined in Chart 4, a similar pattern is encountered. It can be inferred that there exists a strong bidirectional relationship between credit card limits and balance developments. In other words, individuals who need more limits can increase their card balances when they reach this additional limit, and offering higher card limits by banks to individuals can encourage them to spend more.

[Insert Chart 4 Here]

Charts 5 to 8 further show the outlook for nominal balance and limit, and annual changes in balance and limit, respectively. Nominal indicators confirm the existence of a parallel trend relationship between control and treatment groups in the 2015-2022 (pre-2022) period. In the post-2022 period, due to the structure of nominal indicators and the structure of the inflationary period, the realizations were above the periodic average. However, it is observed that the treatment group differs significantly from the control group during this period.

[Insert Charts 5 to 8 Here]

Charts 9 to 12 indicate nominal and real PCC balance and limit as well as annual growth rate in four different limit brackets. The results reveal that there is indeed a parallel trend between control and treatment groups in all limit categories in the pre-2022 period. In the post-2022 period, while different limit categories move in the same direction as the total sample, there are categorical differences. While a relatively limited separation is observed in the trends of the control and treatment groups in the low-limit categories (50-100 thousand TL and 100-200 thousand TL), this separation is seen to be much more evident in the high-limit groups (200-500 thousan TL and 500+ thousand TL). In addition, when the treatment group was examined in the limit categories, it was seen that the balance increases in the post-2022 period are relatively closer to each other in different limit categories (except for the increase in the 500+ thousand TL category in 2024). On the other hand, it is understood that limit increases are much higher in the higher limit categories. This implies that limit increases in low-limit groups occur in a more compatible structure with balance increases.

[Insert Charts 9 to 12 Here]

An alternative method is also preferred to determine the control and treatment groups within the scope of the robustness check. In robustness analyses, the limit increase rate of the median observation was taken as the threshold value for the limit increase (which was termed as $High\,Limit\_Median$ to replace the original binary variable $High\,Limit$), instead of post-2022 inflation. Obtaining similar results in Charts A1 to A10 (of the Appendix) implies that the findings have a robust structure.

In the next phase of our analysis, a formal DiD model is estimated as specified in Equation (1). The baseline DiD results obtained with alternative indicators of PCC movements are given in Table 1. In column (1), the interaction term between $Post$ and $High\,Limit$ is positive and significant implying that the households experiencing a credit card limit increase of more than the recorded cumulative inflation rate after 2022 have displayed a stronger hike in card spending in terms of the natural logarithm of level values, relative to the borrowers in the control group. In columns (2) and (3) of Table 1, the coefficients attached to interactions turn out to be 80.6 and 49.2 (in a significant way), which point out the respective differences of average nominal and real growth rates of PCC balances in the treatment and control groups from pre- to post-2022 episodes. Columns (4) and (5) of Table 1 show the expected impact of limit increases on household expenditures by using the natural logarithm and the level of real PCC balances, whereas column (6) demonstrates a similar effect with the help of unadjusted level values of credit card spending. In this case, despite the fact that meaningful and consistent results are obtained from all indicators, the results for the logarithmic form of nominal PCC balance (ln_PCC) and PCC balance growth (PCC_gr) indicators are presented due to the ease of interpreting the coefficients obtained in other analyses where limit groups and control variables were used. Overall, our findings render support to the argument that limit expansions being not compatible with the macroeconomic outlook are likely to result in excessive credit card spending.

[Insert Table 1 Here]

When we consider different limit brackets and repeat the analysis, as seen in Table 2, we reach the conclusions supporting earlier findings. While the degree of divergence between treatment and control groups is lower in low limit brackets, it is seen that the coefficient is roughly higher in limit brackets over 200 thousand TL. These results are valid for both the logarithmic form of nominal PCC balance and PCC balance growth.

[Insert Table 2 Here]

In Table 3, we undertake an investigation of whether the difference between the treatment and control groups turns out to be significant in the pre-2022 period. The results in the 2020-2021 columns are obtained by excluding the observations of 2022 and subsequent years. In this setting, the years 2020-2021 are considered post-period and 2015-2019 are considered pre-period. Using a similar method, results for the 2019-2020 and 2018-2019 columns were also obtained. The results show that the households in treatment and control groups indeed did not differ significantly from each other in the post- and pre-periods comparison before 2023. These findings also indirectly support the parallel trend inferences given in Charts 1 to 6 and the related robustness checks.

[Insert Table 3 Here]

In Table 4, we check whether baseline results change considerably when we include a specific set of control variables. To control the demand forces concerning credit cards via individual income, we utilize a proxy of the disposable income (of the households). On the other hand, the Herfindahl-Hirschman Index (HHI) was used to control the supply of credit cards through the competition of banks in the market. While HHI takes different values for each year, disposable income has different values for each year and each limit group. While the results confirm the robust structure of the baseline results, the control variables also provide significant findings. The coefficients on HHI parameter assume a negative sign implying a slowdown in credit card balance or balance growth as competition in the credit card market decreases (as HHI value increases). On the other hand, the positive coefficients on disposable income parameter indicate that income increase triggers an upward movement in credit card balance or balance growth rate.

[Insert Table 4 Here]

In Table 5, we consider the balance for credit card installments as the outcome variable.[8] These results turn out to be compatible with the baseline findings in the scope of both aggregate approach and specific analysis involving limit brackets. The results show that the treatment group's installment expenditures diverge significantly in the post-2022 period. In Table 6, we add the aforementioned control variables when predicting card installments. Similar to prior results, the coefficients referring to the treatment effect remain expectedly positive and significant. In robustness analyses, the limit increase rate of the median observation is taken as the threshold value for treatment allocation, instead of post-2022 inflation. We get similar results in Tables A1 to A5 (of the Appendix).

[Insert Tables 5 and 6 Here]

As an additional robustness check, we implement a series of placebo tests to evaluate the validity of our baseline inferences. In this context, we employ the method outlined by Heß (2017). In the first case, we consider the model specified in Equation (1) and take the natural logarithm of PCC balance (ln_PCC) as the outcome variable. Keeping the treatment period the same, we bootstrap 1000 different samples by randomly assigning the treatment status across individual borrowers and repeating the estimations to record the pseudo treatment effects. Chart A11 in the Appendix displays the empirical distribution of DiD coefficients from those repetitions. As it is seen in the graphical representation, the actual coefficient (presented in column (1) of Table 1 as mentioned before) which is 0.66 is not covered by the randomized set of coefficients. Next, we consider a similar model specification by taking the outcome variable of the growth rate of card balances (PCC_gr). Following the same randomization inference procedure with 1000 repetitions, we present the empirical distribution of pseudo coefficients in Chart A12 of the Appendix. Similar to an earlier case, the actual coefficient (80.6) is vastly differentiated from the pseudo coefficient distribution. These findings render further support to the validity of the parallel trend assumption in our design.

[8] Since the possibility of using credit cards in installments can play an important role in influencing the consumption decisions of cardholders, it is important to include installment usage in the study findings. Since only the installment balance information is included in the micro data, unfortunately, the findings regarding the number of installments are not included in the analysis.

4. Conclusion

PCC products have gained an important share in total household indebtedness in recent years. Besides the rising trend of credit card use among Turkish households, such services of financial intermediaries have been a focal point of the design of macroprudential policies including but not limited to installment restrictions. A recent observation applicable to the Turkish setting in the post-Covid period is the notable and widespread increase in credit card limits under the phase of inflationary shocks. These recent developments paved the way for a plausible empirical design to investigate an important relationship discussed by the previous literature, which is the relationship between credit card limits and household consumption, given that the related upward revisions in credit card limits had not been uniform and provided a desired level of variation for the case of Turkish households.

With the aforementioned motivation, this paper investigates the relationship between credit card limits and spending trends by using micro-level credit card balance information for the period 2015-2024 obtained from the Credit Registry (available in CBRT) and variation in limit changes in the last inflationary episode. Our design considers the individual borrowers with a rise in card limits above the realized inflation rate (between 2022 and 2024) within the treated group for which the card spending behavior is contrasted with an accompanying control group characterized by a limit increase below the inflation rate. Our baseline findings show that the individuals facing higher limit expansions engage in higher PCC spending levels and stronger PCC spending growth rates in both nominal and real terms, relative to the control group, after accounting for individual borrower- and time-fixed effects. We further demonstrate the internal validity of empirical design by performing the graphical evaluation of spending patterns for individuals with and without amplified limits. These findings are robust to additional tests including placebo analysis and the inclusion of other control variables. Our extended estimations imply that individuals classified in higher limit brackets before the occurrence of shock in 2022 (at the same time benefiting from higher limit increases during 2022-2024) enjoy higher elevation in card spending. Last but not least, we find that credit card installment payments are similarly positively affected by limit increases.

Our empirical analysis provides valuable insights in terms of policymaking. First, we hint at a causal relationship between card limits and household consumption. In turn, this implies that, in addition to installment restrictions and interest rate adjustments, a potential way to avoid financial stability concerns in the case of Türkiye due to the excessive growth in this sub-segment of retail loans is to monitoring and regulating the card limits imposed by commercial banks. Second, we openly argue that a particular component of heightened household consumption during the recent phase coinciding with unprecedented inflationary shocks is the unhindered steps taken by the banks to increase credit card limits. Therefore, card limits being increased in line with the macroeconomic conjuncture might lower the upward inflationary pressures and possible current account imbalances in addition to financial instability during times of macroeconomic volatility and uncertainty. In other words, when increasing card limits, it is important to take into account inflation developments as well as individuals' incomes for the stable course of macroeconomic indicators.

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Charts

Chart 1: Household Indebtedness in Peer Countries (Debt/GDP, %)

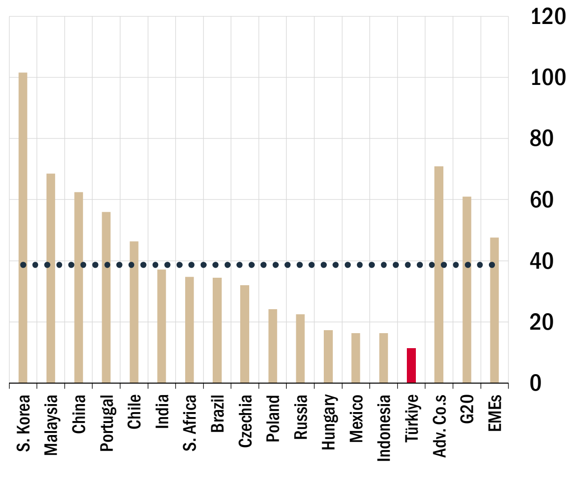
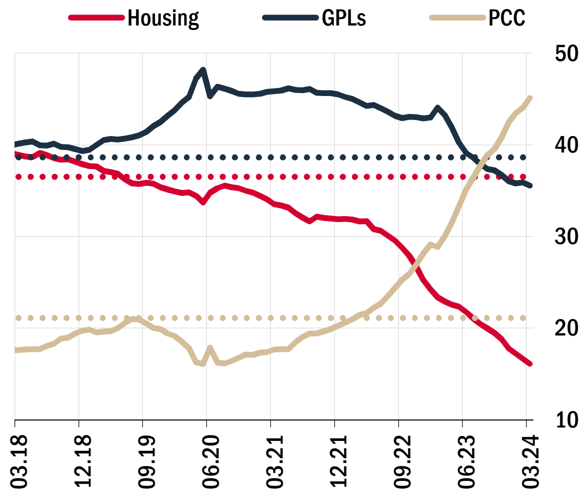


Chart 2: Breakdown of Households' Financial Liabilities (%)

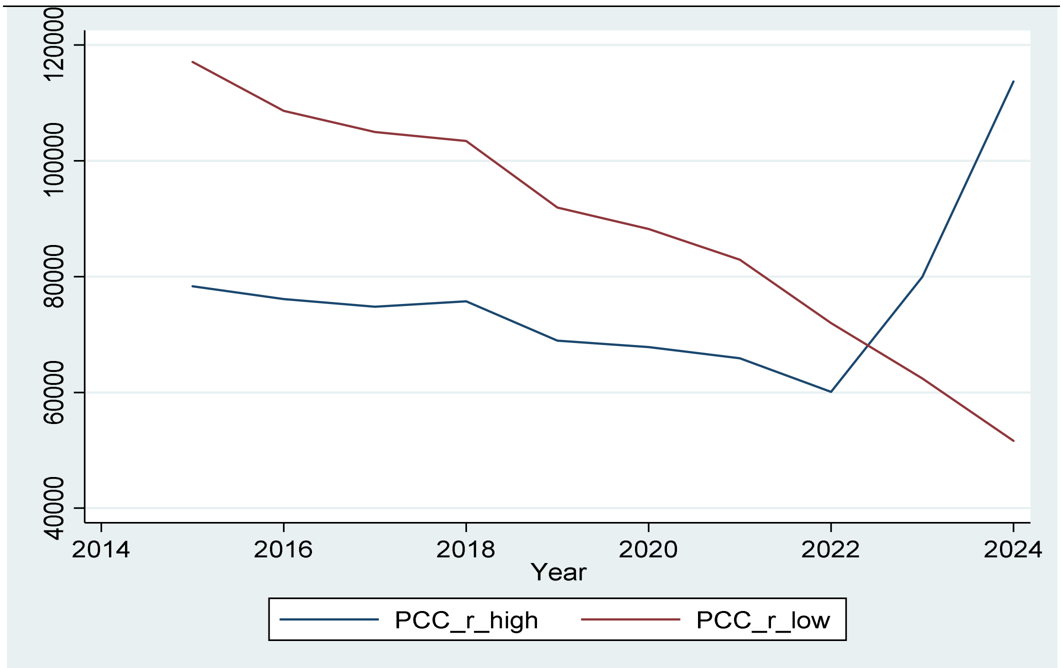


Source: BIS Date of Observation: 2023 Q3

Source: BRSA Last Observation: 03.24

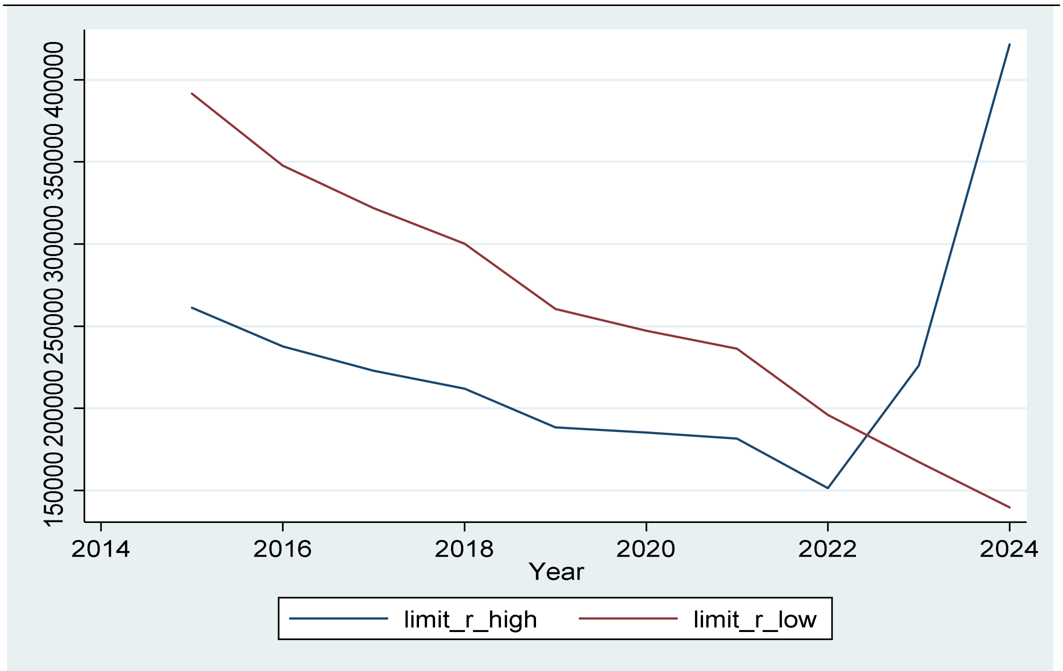
Notes: Household indebtedness is calculated as the ratio of the total debt securities and loans of households and nonprofit institutions serving households to GDP. The horizontal line in Chart 1 shows the average values of selected countries. The dashed lines in Chart 2 are the average values of the related series for 2012-2019.

Chart 3: Real PCC Balance Development of Control and Treatment Groups



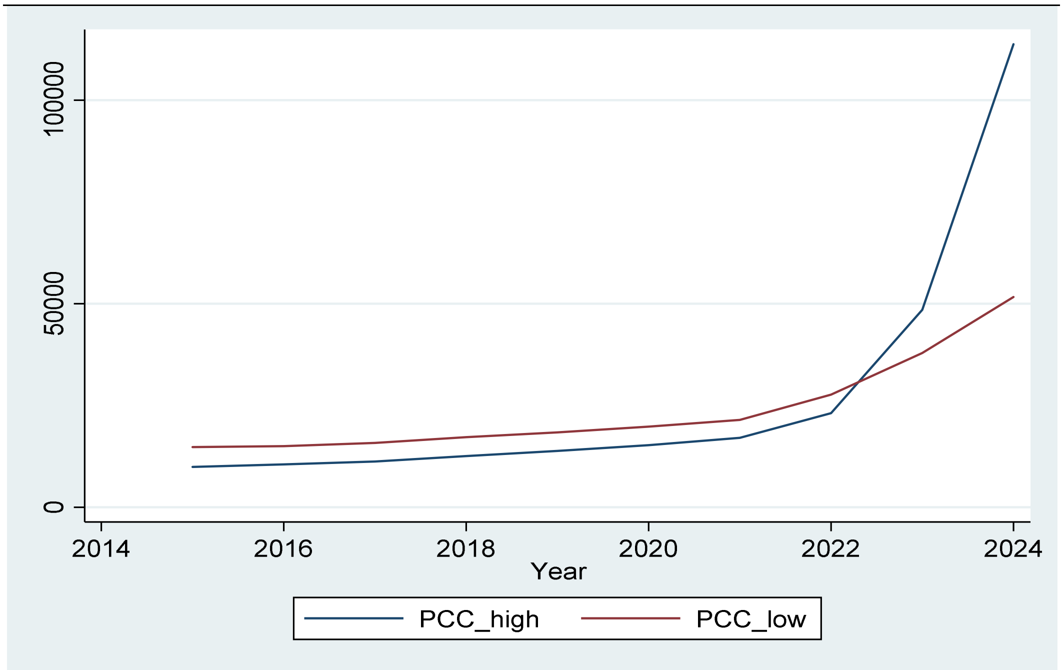
Notes: PCC_r_high: treatment group, PCC_r_low: control group. The values on the chart are the average real credit card balance of the relevant group in the relevant years. The post-2022 inflation was taken as the threshold value for the limit increase.

Chart 4: Real PCC Limit Development of Control and Treatment Groups



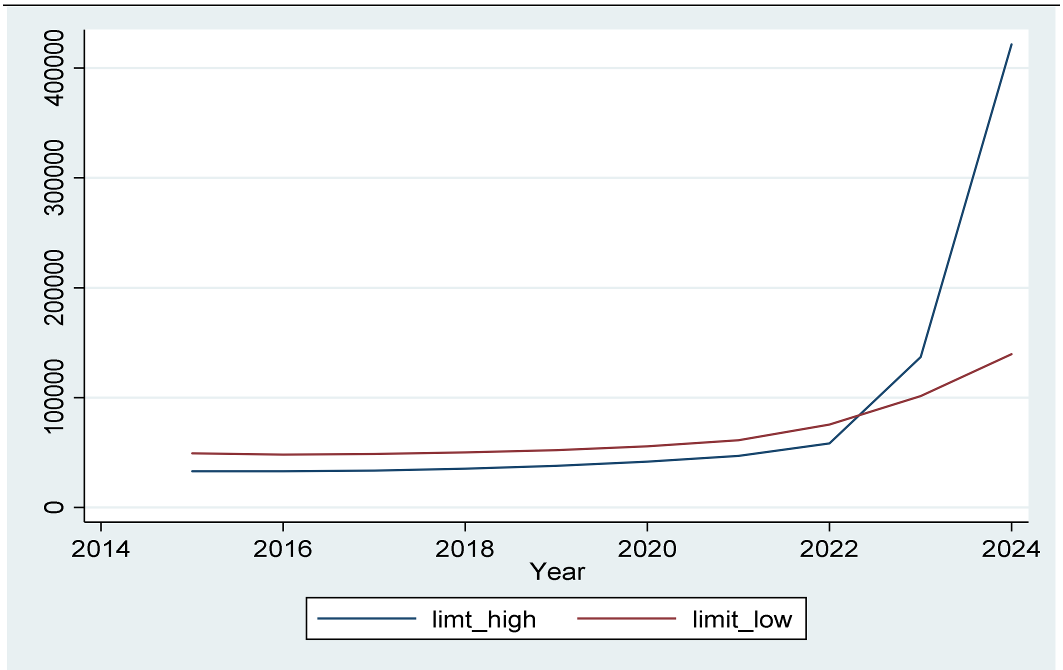
Notes: limit_r_high: treatment group, limit_r_low: control group. The values on the chart are the average real credit card limit of the relevant group in the relevant years. The post-2022 inflation was taken as the threshold value for the limit increase.

Chart 5: Nominal PCC Balance Development of Control and Treatment Groups



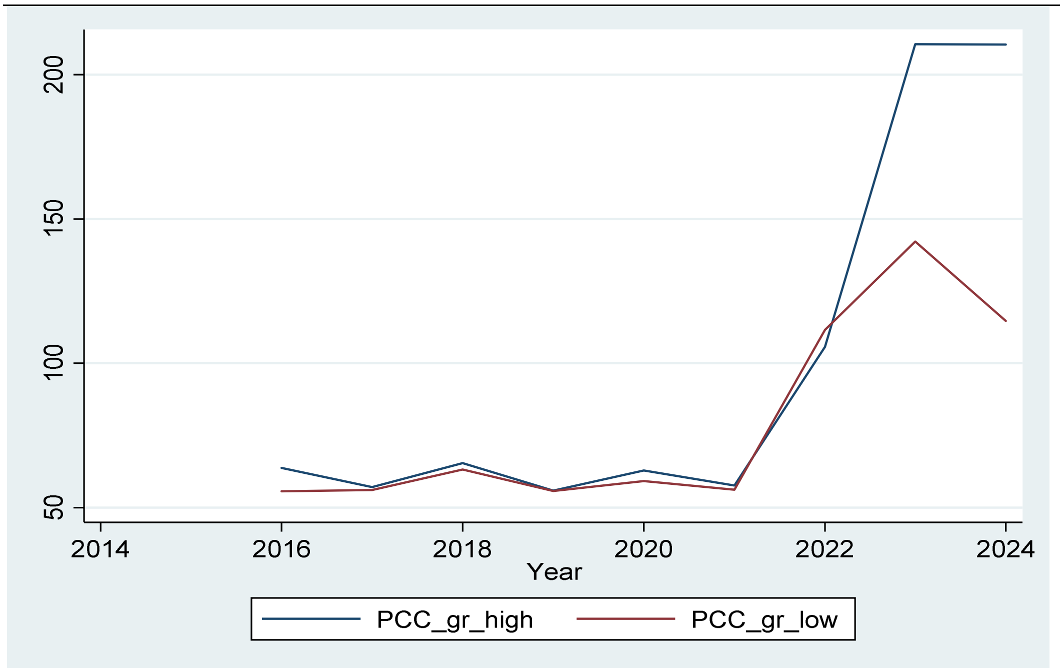
Notes: PCC_high: treatment group, PCC_low: control group. The values on the chart are the average nominal credit card balance of the relevant group in the relevant years. The post-2022 inflation was taken as the threshold value for the limit increase.

Chart 6: Nominal PCC Limit Development of Control and Treatment Groups



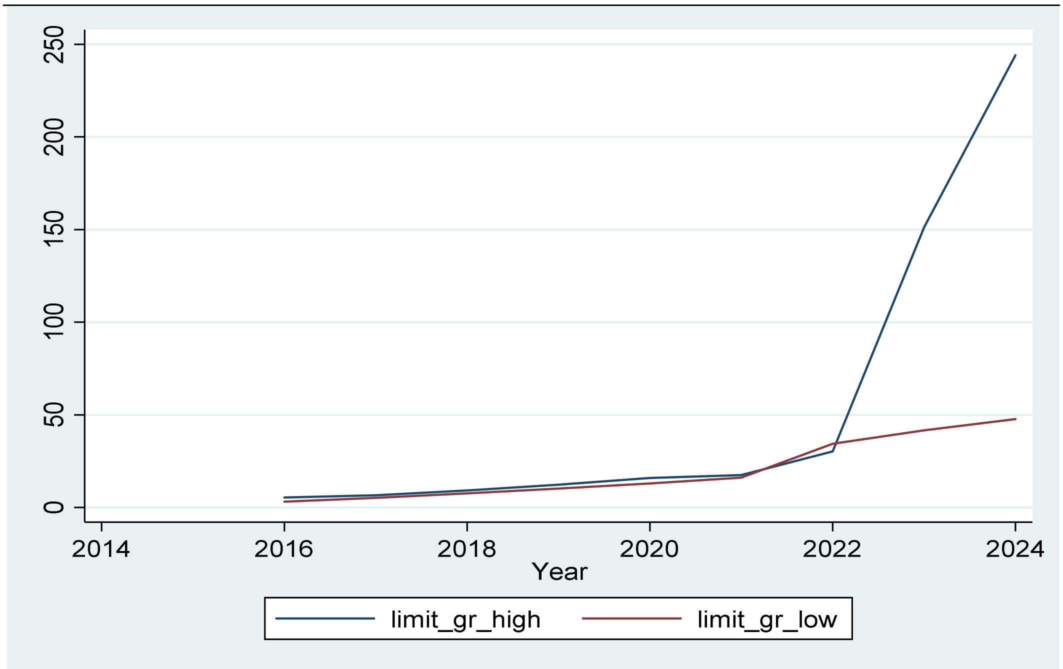
Notes: limit_high: treatment group, limit_low: control group. The values on the chart are the average nominal credit card limit of the relevant group in the relevant years. The post-2022 inflation was taken as the threshold value for the limit increase.

Chart 7: Nominal PCC Balance Growth of Control and Treatment Groups



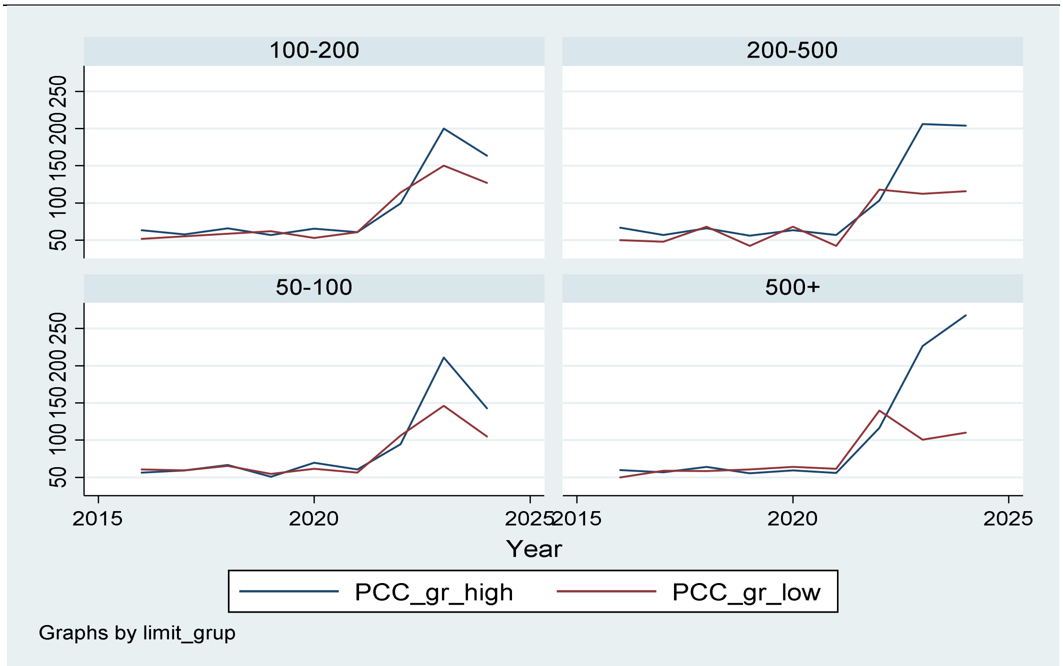
Notes: PCC_gr_high: treatment group, PCC_gr_low: control group. The values on the chart are the average yearly growth of the nominal credit card balance of the relevant group in the relevant years. Series are winsorized at 1st and 99th percentiles to minimize the impact of outliers. The post-2022 inflation was taken as the threshold value for the limit increase.

Chart 8: Nominal PCC Limit Growth of Control and Treatment Groups



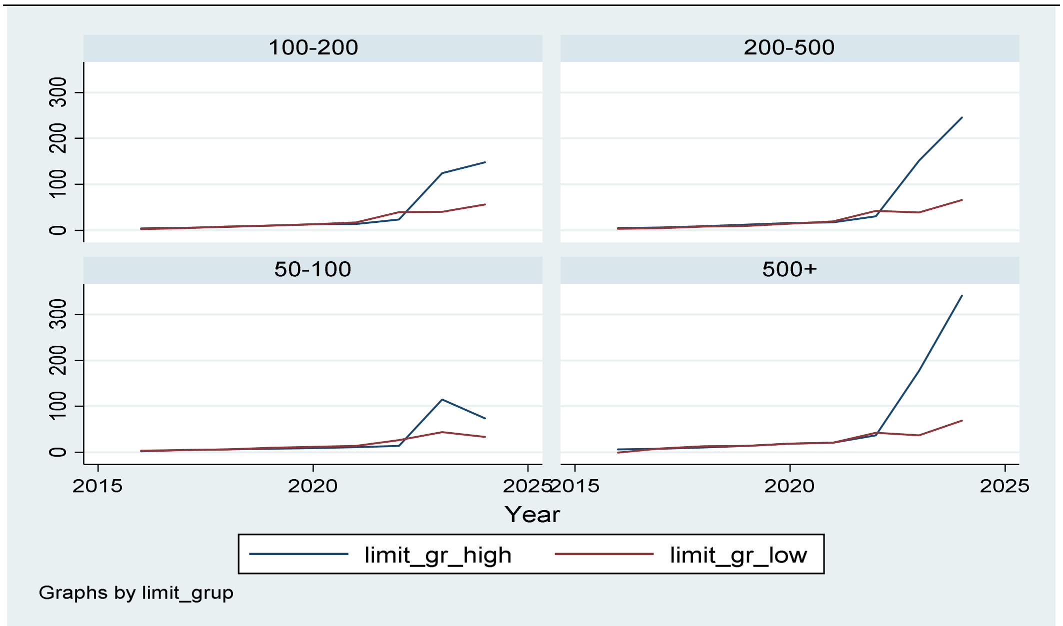
Notes: limit_gr_high: treatment group, limit_gr_low: control group. The values on the chart are the average yearly growth of the nominal credit card limit of the relevant group in the relevant years. Series are winsorized at 1st and 99th percentiles to minimize the impact of outliers. The post-2022 inflation was taken as the threshold value for the limit increase.

Chart 9: Nominal PCC Balance Growth of Control and Treatment Groups in Different Limit Categories



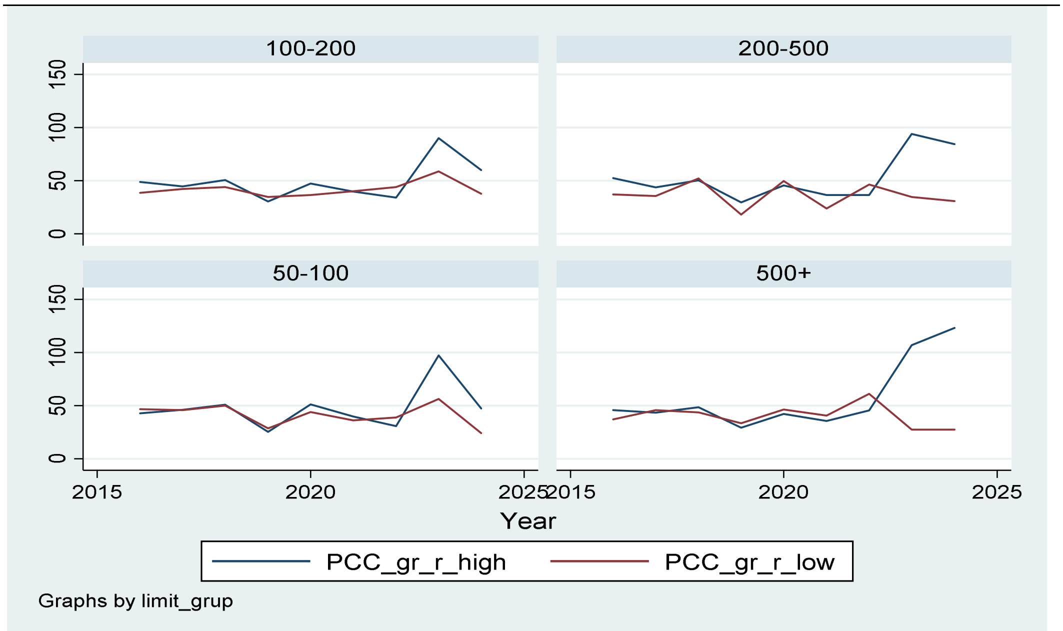
Notes: PCC_gr_high: treatment group, PCC_gr_low: control group. The values on the chart are the average yearly growth of credit card balances of the relevant group and years. Limit categories were created based on January 2024 data. The post-2022 inflation was taken as the threshold value for the limit increase.

Chart 10: Nominal PCC Limit Growth of Control and Treatment Groups in Different Limit Categories



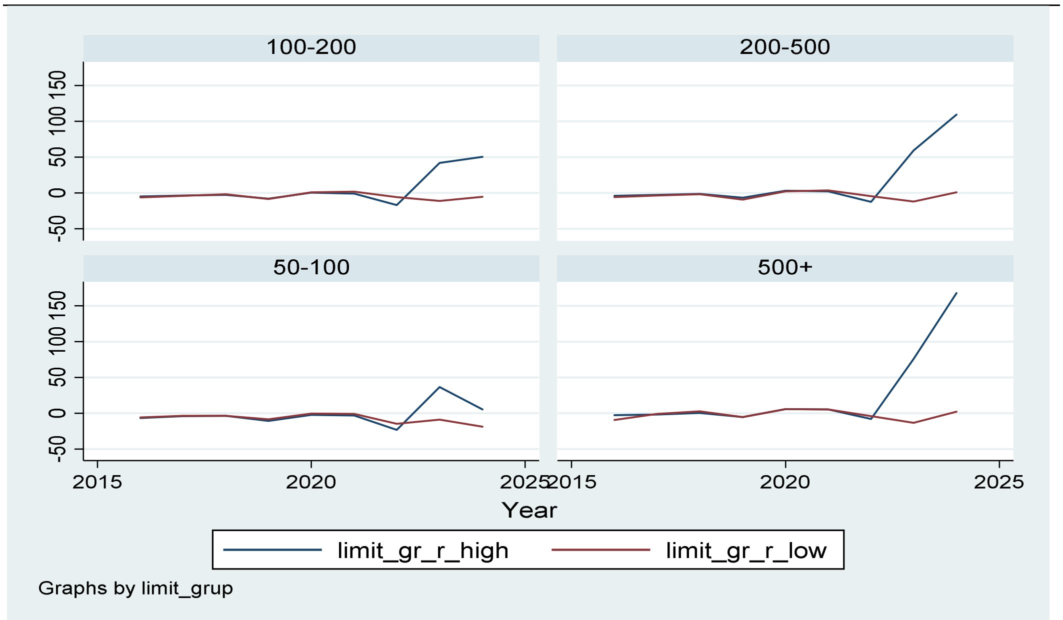
Notes: limt_gr_high: treatment group, limit_gr_low: control group. The values on the chart are the average yearly growth of credit card limits of the relevant group and years. Limit categories were created based on January 2024 data. The post-2022 inflation was taken as the threshold value for the limit increase.

Chart 11: Real PCC Balance Growth of Control and Treatment Groups in Different Limit Categories



Notes: PCC_gr_r_high: treatment group, PCC_gr_r_low: control group. The values on the chart are the average yearly growth of credit card balances of the relevant group and years. Limit categories were created based on January 2024 data. The post-2022 inflation was taken as the threshold value for the limit increase.

Chart 12: Real PCC Limit Growth of Control and Treatment Groups in Different Limit Categories



Notes: limit_gr_r_high: treatment group, limit_gr_r_low: control group. The values on the chart are the average yearly growth of credit card limits of the relevant group and years. Limit categories were created based on January 2024 data. The post-2022 inflation was taken as the threshold value for the limit increase.

Tables

Table 1: Baseline DiD Results

	(1) ln_PCC	(2) PCC_gr	(3) PCC_r_gr	(4) ln_PCC_r	(5) PCC_r	(6) PCC
Post x High Limit	0.660***	80.6***	49.2***	0.660***	64,964***	40,931***
	(0.013)	(3.045)	(1.942)	(0.013)	(1,286.2)	(659.8)
Observations	655,750	590,175	590,175	655,750	655,750	655,750
Credit Card User FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.700	0.145	0.109	0.598	0.635	0.439

Notes: Standard errors clustered at the credit card user level are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.10

Table 2: DiD Results with PCC Limit Brackets

	(1) ln_PCC				(2) PCC_gr			
	50-100	**100-200**	**200-500**	**500+**	**50-100**	**100-200**	**200-500**	**500+**
Post x High Limit	0.343***	0.392***	0.586***	0.733***	52.2***	41.4***	86.5***	145.6***
	(0.026)	(0.021)	(0.033)	(0.094)	(7.0)	(5.3)	(6.7)	(16.5)
Observations	52,330	157,650	282,380	163,390	47,097	141,885	254,142	147,051
Credit Card User FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.593	0.633	0.675	0.741	0.119	0.127	0.144	0.173

Notes: Standard errors clustered at the credit card user level are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.10

Table 3: DiD Results for pre-2022 Period

	(1) PCC_gr			(2) PCC_r_gr		
	2020-21	**2019-20**	**2018-19**	**2020-21**	**2019-20**	**2018-19**
Post x High Limit_20	-0.311			-0.348		
	(1.911)			(1.686)		
Post x High Limit_19		-1.906			-1.777	
		(1.977)			(1.742)	
Post x High Limit_18			-3.417			-3.130
			(2.268)			(2.031)
Observations	393,450	327,875	262,300	393,450	327,875	262,300
Credit Card User FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.134	0.158	0.197	0.135	0.160	0.197

Notes: Standard errors clustered at the credit card user level are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.10

Table 4: DiD Results with Control Variables

	(1) ln_PCC				(2) PCC_gr			
Post x High Limit	0.660*** (0.013)	0.481*** (0.013)	0.660*** (0.013)	0.574*** (0.013)	80.6*** (3.045)	59.8*** (3.152)	80.6*** (3.045)	66.7*** (3.067)
ln_hhi			-11.5*** (0.061)	0.477*** (0.075)				
post			0.866*** (0.012)	-0.252*** (0.013)			63.4*** (2.860)	-10.6*** (3.533)
ln_disp_inc		2.147*** (0.038)		1.04*** (0.006)				
disp_inc_gr						3.0*** (0.128)		2.0*** (0.051)
hhi_gr							-0.338 (0.238)	-2.810*** (0.221)
Observations	655,750	655,750	655,750	655,750	590,175	590,175	590,175	590,175
Credit Card User FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	No	No	Yes	Yes	No	No
R-squared	0.700	0.703	0.678	0.700	0.145	0.146	0.141	0.144

Notes: Standard errors clustered at the credit card user level are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.10

Table 5: DiD Results for PCC Installments with Limit Brackets

	(1) ln_inst	(2) inst_gr	(3) ln_inst				(4) inst_gr			
			50-100	**100-200**	**200-500**	**500+**	**50-100**	**100-200**	**200-500**	**500+**
Post x High Limit	0.700*** (0.015)	125.1*** (8.8)	0.360*** (0.033)	0.467*** (0.026)	0.741*** (0.040)	0.855*** (0.097)	108.9*** (20.5)	78.6*** (15.9)	138.7*** (20.2)	196.9*** (62.5)
Observations	588,126	530,526	44,879	137,973	254,931	150,343	40,494	124,116	230,260	135,656
Credit Card User FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.568	0.135	0.467	0.498	0.535	0.600	0.128	0.132	0.134	0.143

Notes: Standard errors clustered at the credit card user level are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.10

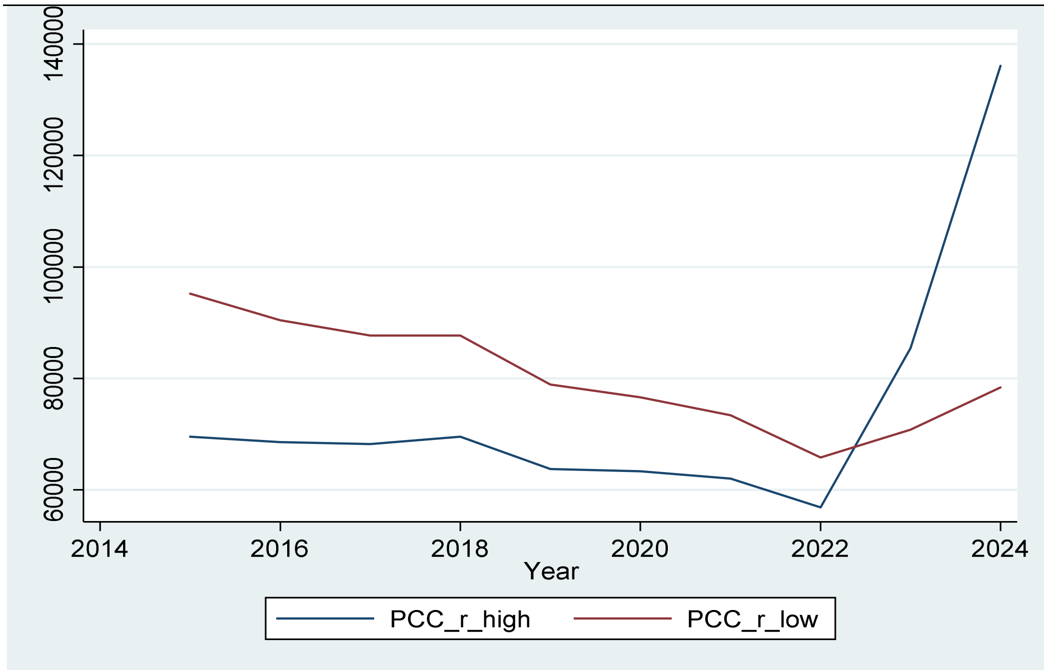
Table 6: DiD Results for PCC Installments with Control Variables

	(1) ln_inst			
Post x High Limit	0.700*** (0.015)	0.556*** (0.016)	0.702*** (0.015)	0.643*** (0.015)
ln_hhi			-9.921*** (0.085)	-1.875*** (0.111)
post			0.782*** (0.015)	0.032* (0.017)
ln_disp_inc		1.745*** (0.053)		0.698*** (0.007)
Observations	588,126	588,126	588,126	588,126
Credit Card User FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	No	No
R-squared	0.568	0.569	0.560	0.567

Notes: Standard errors clustered at the credit card user level are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.10

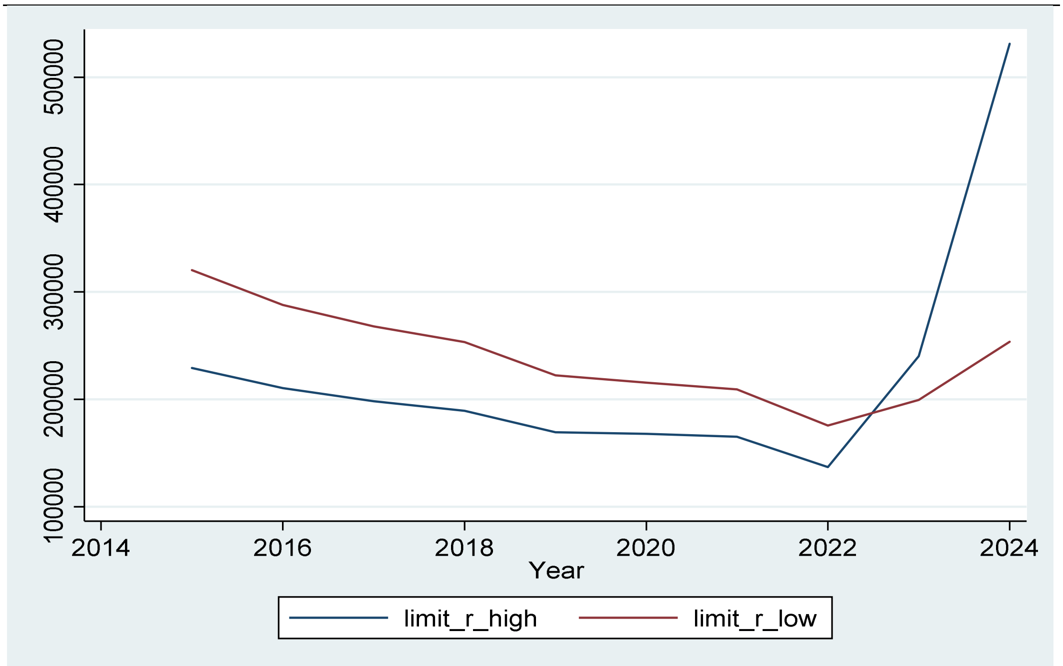
Appendix

Chart A1: Real PCC Balance Development of Control and Treatment Groups



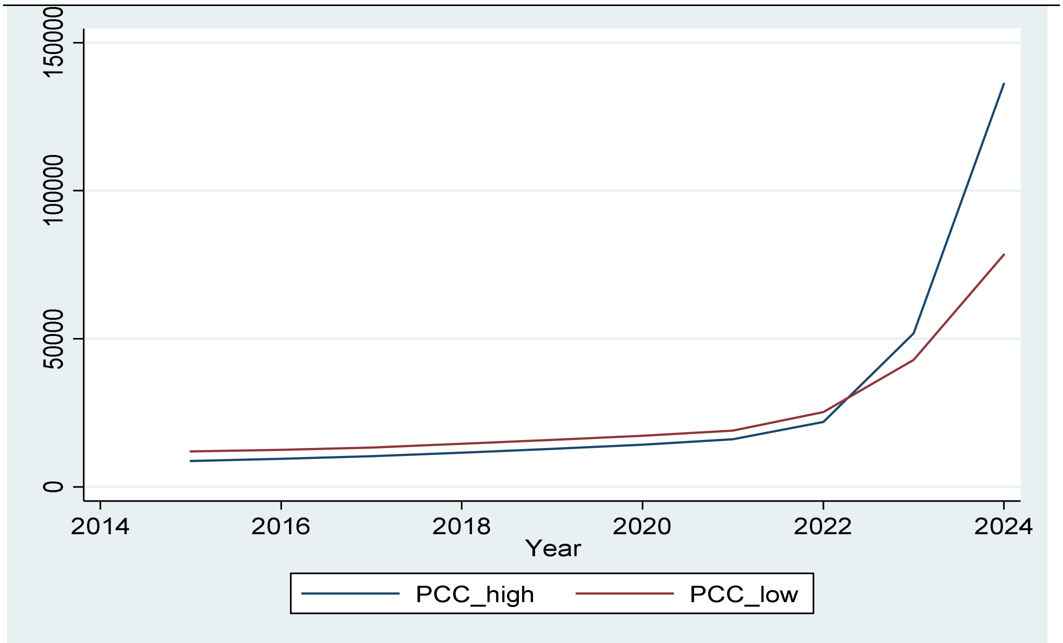
Notes: PCC_r_high: treatment group, PCC_r_low: control group. The values on the chart are the average real credit card balance of the relevant group in the relevant years. The limit increase rate of the median observation was taken as the threshold value for the limit increase.

Chart A2: Real PCC Limit Development of Control and Treatment Groups



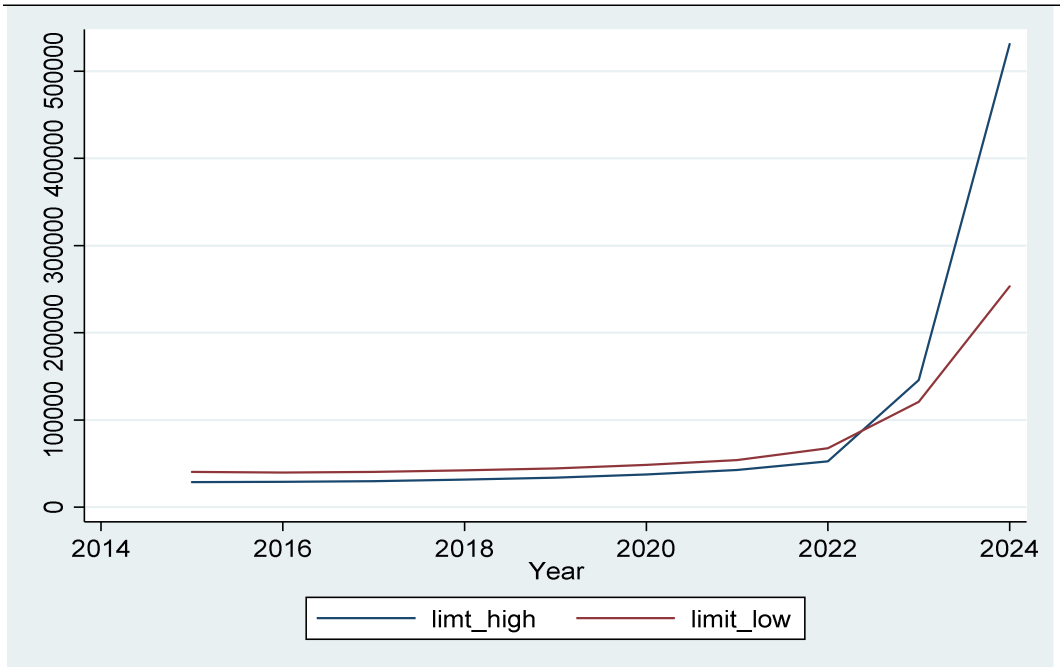
Notes: limit_r_high: treatment group, limit_r_low: control group. The values on the chart are the average real credit card limit of the relevant group in the relevant years. The limit increase rate of the median observation was taken as the threshold value for the limit increase.

Chart A3: Nominal PCC Balance Development of Control and Treatment Groups



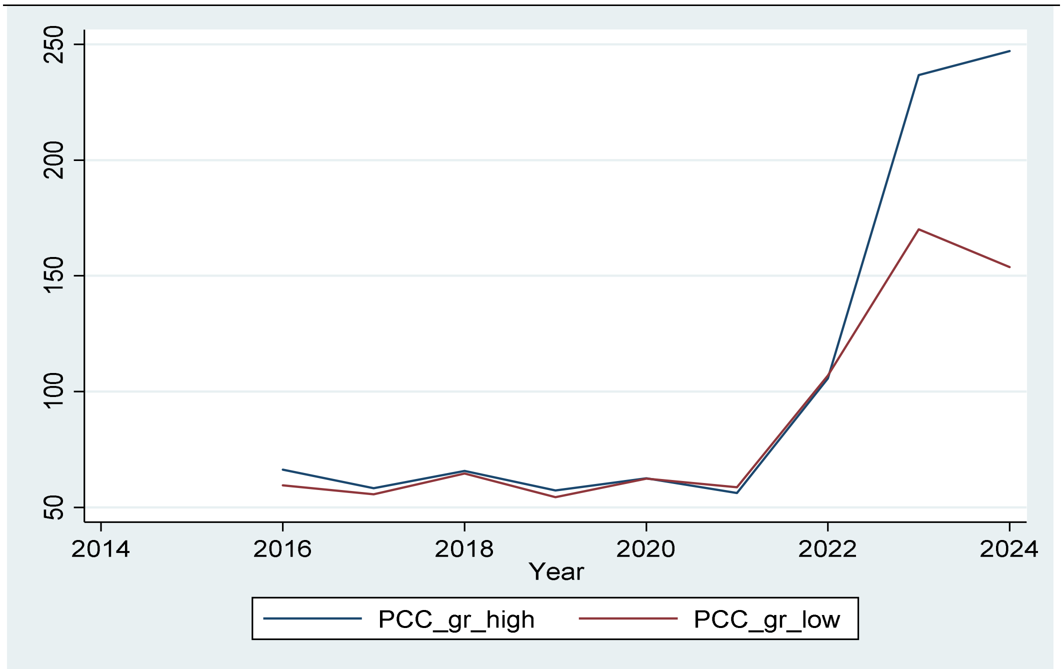
Notes: PCC_high: treatment group, PCC_low: control group. The values on the chart are the average nominal credit card balance of the relevant group in the relevant years. The limit increase rate of the median observation was taken as the threshold value for the limit increase.

Chart A4: Nominal PCC Limit Development of Control and Treatment Groups



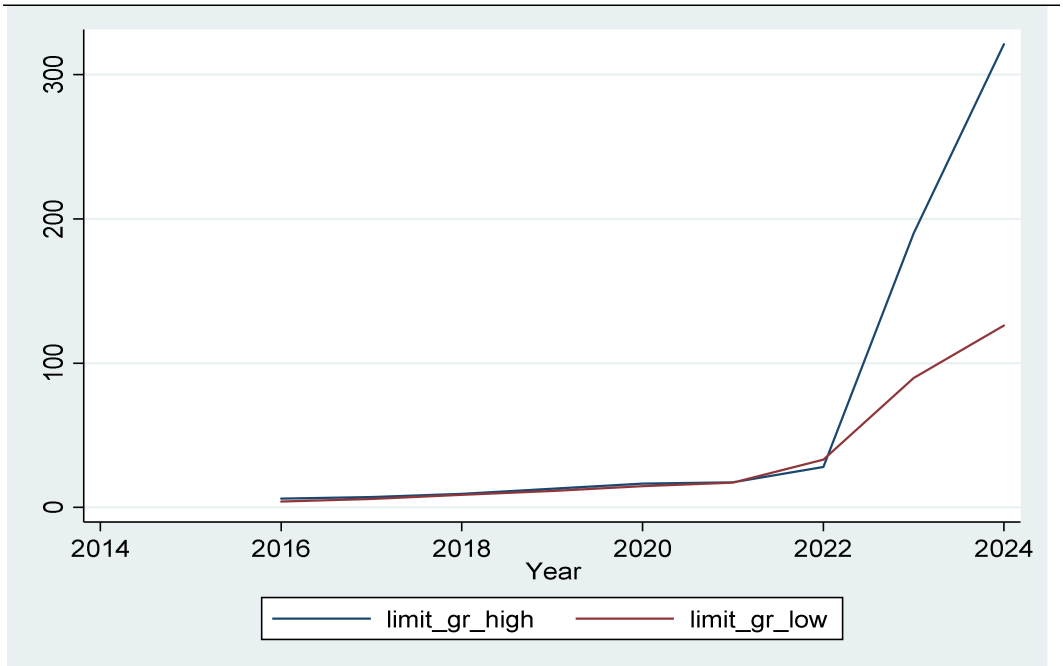
Notes: limit_high: treatment group, limit_low: control group. The values on the chart are the average nominal credit card limit of the relevant group in the relevant years. The limit increase rate of the median observation was taken as the threshold value for the limit increase.

Chart A5: Nominal PCC Balance Growth of Control and Treatment Groups



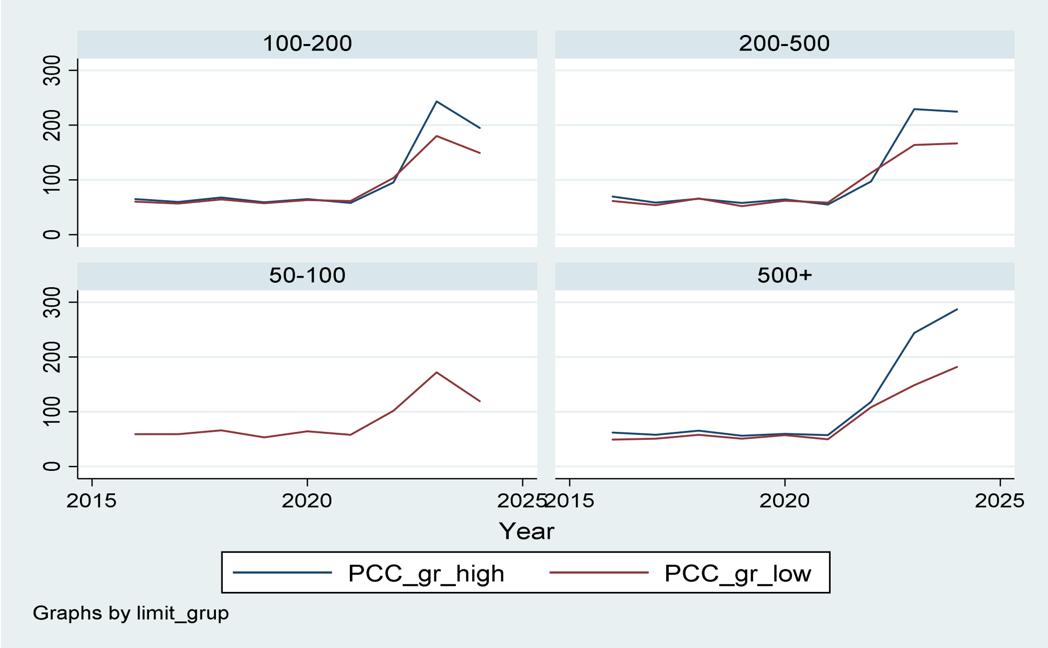
Notes: PCC_gr_high: treatment group, PCC_gr_low: control group. The values on the chart are the average yearly growth nominal credit card balance of the relevant group in the relevant years. Series are winsorized at 1st and 99th percentiles to minimize the impact of outliers. The limit increase rate of the median observation was taken as the threshold value for the limit increase.

Chart A6: Nominal PCC Limit Growth of Control and Treatment Groups



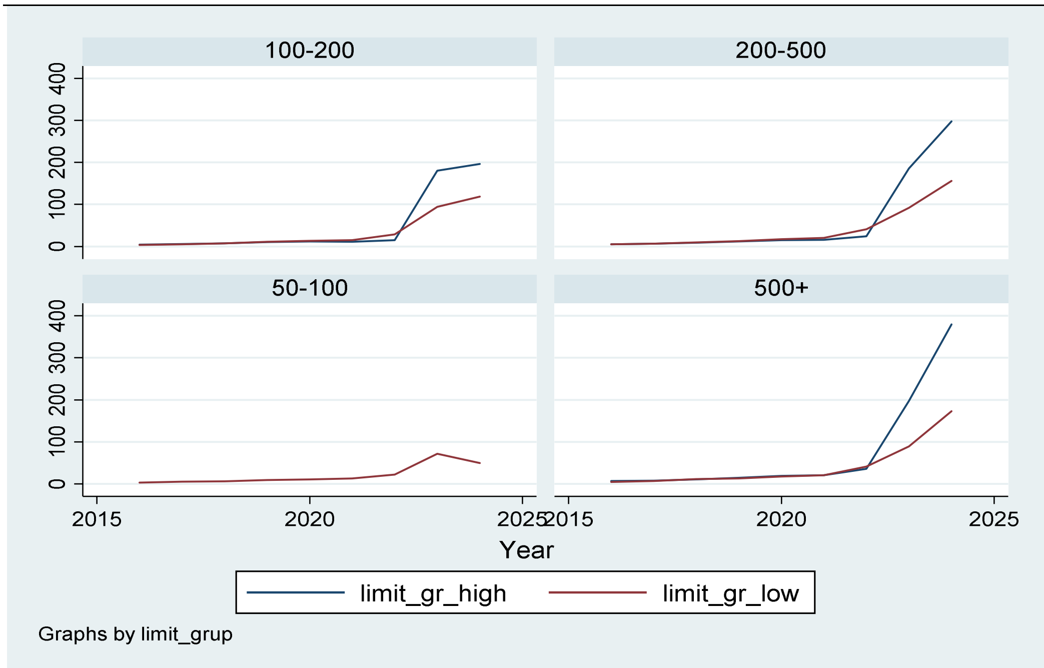
Notes: limit_gr_high: treatment group, limit_gr_low: control group. The values on the chart are the average real credit card balance of the relevant group in the relevant years. Series are winsorized at 1st and 99th percentiles to minimize the impact of outliers. The limit increase rate of the median observation was taken as the threshold value for the limit increase.

Chart A7: Nominal PCC Balance Growth of Control and Treatment Groups in Different Limit Categories



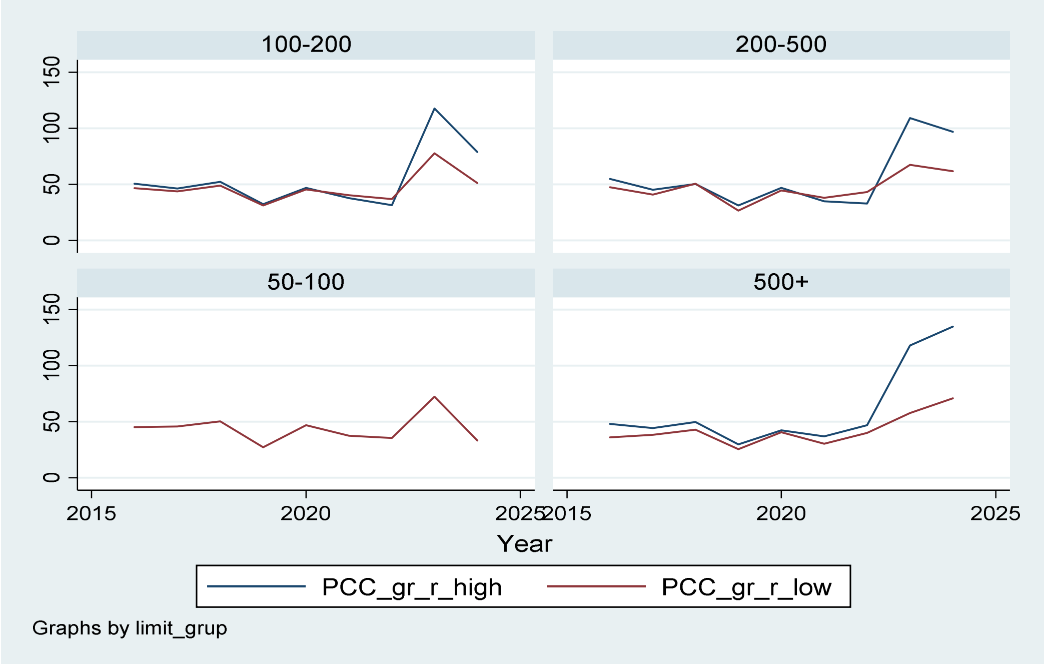
Notes: PCC_gr_high: treatment group, PCC_gr_low: control group. The values on the chart are the average yearly growth credit card balance of the relevant group and years. Limit categories were created based on January 2024 data. The limit increase rate of the median observation was taken as the threshold value for the limit increase.

Chart A8: Nominal PCC Limit Growth of Control and Treatment Groups in Different Limit Categories



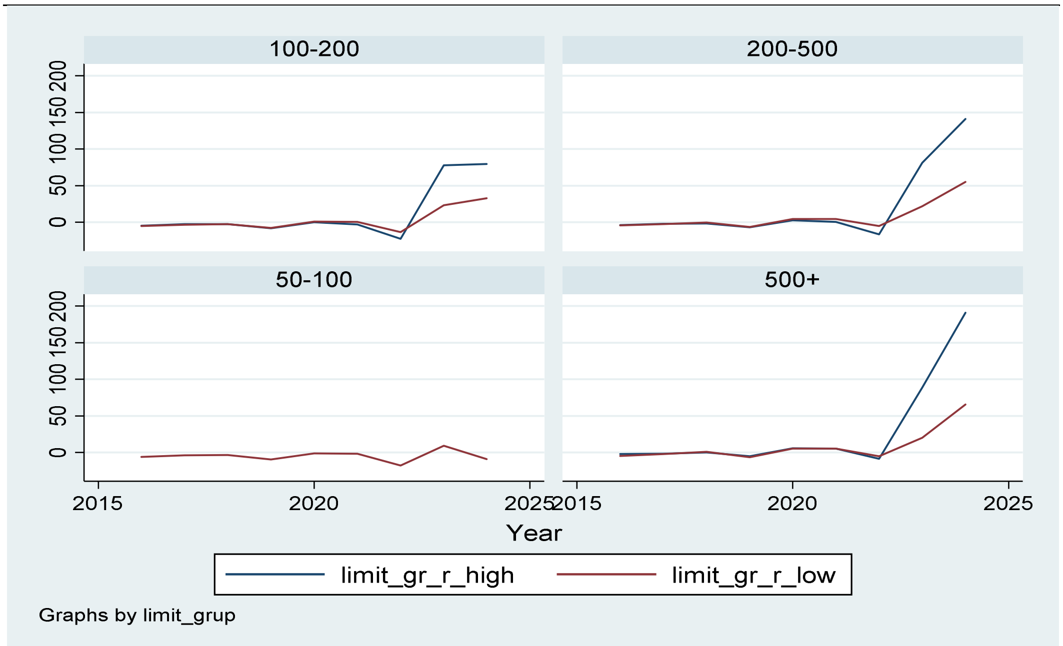
Notes: limt_gr_high: treatment group, limit_gr_low: control group. The values on the chart are the average yearly growth credit card limit of the relevant group and years. Limit categories were created based on January 2024 data. The limit increase rate of the median observation was taken as the threshold value for the limit increase.

Chart A9: Real PCC Balance Growth of Control and Treatment Groups in Different Limit Categories



Notes: PCC_gr_r_high: treatment group, PCC_gr_r_low: control group. The values on the chart are the average yearly growth credit card balance of the relevant group and years. Limit categories were created based on January 2024 data. The limit increase rate of the median observation was taken as the threshold value for the limit increase.

Chart A10: Real PCC Limit Growth of Control and Treatment Groups in Different Limit Categories



Notes: limit_gr_r_high: treatment group, limit_gr_r_low: control group. The values on the chart are the average yearly growth credit card limit of the relevant group and years. Limit categories were created based on January 2024 data. The limit increase rate of the median observation was taken as the threshold value for the limit increase.

Chart A11: Randomization Inference (ln_PCC)

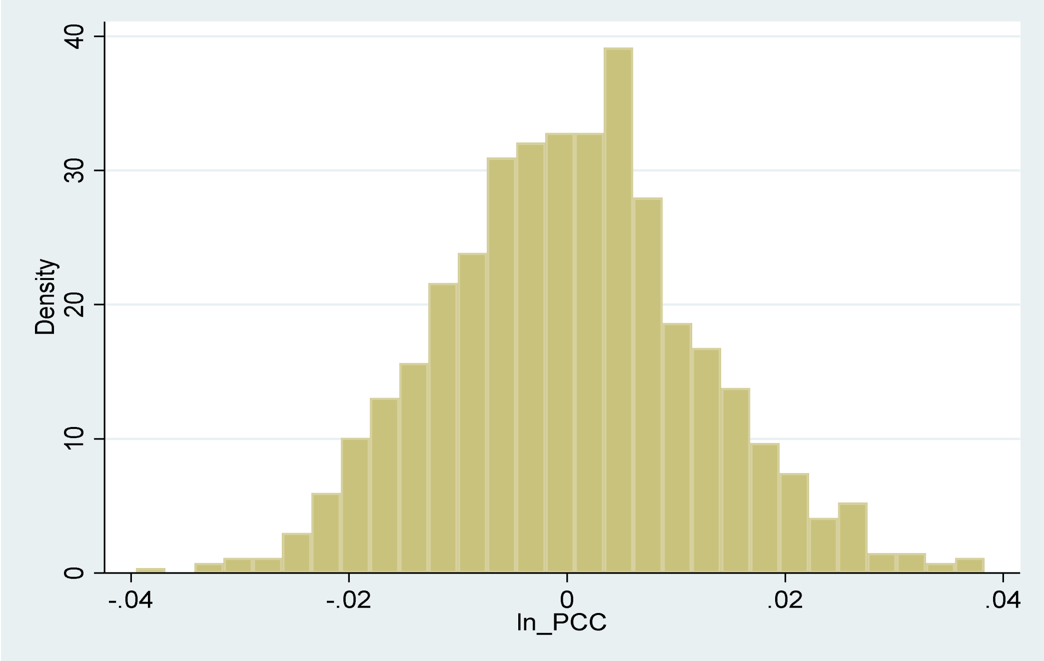


Chart A12: Randomization Inference (PCC_gr)

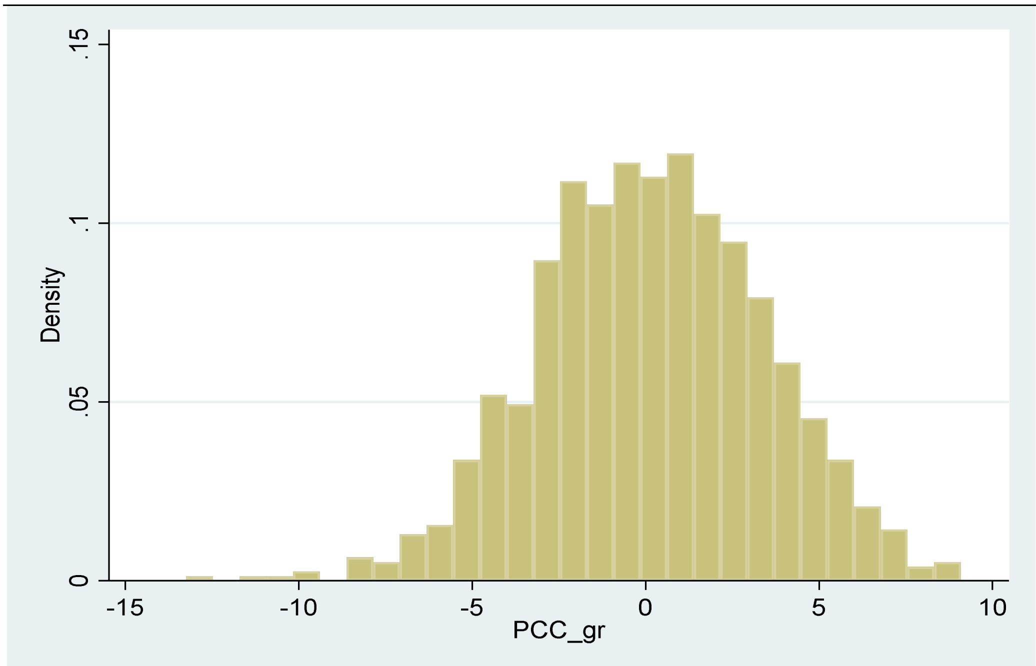


Table A1: Baseline DiD Results

	(1) ln_PCC	(2) PCC_gr	(3) PCC_r_gr	(4) ln_PCC_r	(5) PCC_r	(6) PCC
Post x High Limit_Median	0.494*** (0.007)	78.5*** (2.0)	48.1*** (1.3)	0.494*** (0.007)	52,927*** (782.2)	36,377*** (724.6)
Observations	655,750	590,175	590,175	655,750	655,750	655,750
Credit Card User FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.702	0.147	0.111	0.600	0.639	0.446

Notes: Standard errors clustered at the credit card user level are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.10

Table A2: DiD Results with PCC Limit Brackets

	(1) ln_PCC			(2) PCC_gr		
	100-200	**200-500**	**500+**	**100-200**	**200-500**	**500+**
Post x High Limit_Median	0.247*** (0.018)	0.312*** (0.011)	0.490*** (0.018)	54.0*** (5.3)	61.6*** (3.0)	92.9*** (4.6)
Observations	157,650	282,380	163,390	141,885	254,142	147,051
Credit Card User FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.633	0.675	0.741	0.127	0.144	0.173

Notes: Standard errors clustered at the credit card user level are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.10

Table A3: DiD Results with Control Variables

	(1) ln_PCC				(2) PCC_gr			
Post x High Limit_Median	0.494*** (0.007)	0.361*** (0.007)	0.494*** (0.007)	0.419*** (0.007)	78.5*** (2.0)	66.3*** (2.1)	78.5*** (2.0)	68.1*** (2.0)
ln_hhi			-11.5*** (0.061)	0.324*** (0.075)				
post			1.211*** (0.005)	0.068*** (0.007)			96.3*** (1.3)	23.6*** (2.6)
ln_disp_inc		1.8*** (0.040)		1.027*** (0.006)				
disp_inc_gr						2.1*** (0.129)		1.8*** (0.051)
hhi_gr							-0.338 (0.238)	-2.6*** (0.220)
Observations	655,750	655,750	655,750	655,750	590,175	590,175	590,175	590,175
Credit Card User FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	No	No	Yes	Yes	No	No
R-squared	0.702	0.704	0.680	0.701	0.147	0.148	0.144	0.146

Notes: Standard errors clustered at the credit card user level are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.10

Table A4: DiD Results for PCC Installments with Limit Brackets

	(1) ln_inst	(2) inst_gr	(3) ln_inst			(4) inst_gr		
			100-200	**200-500**	**500+**	**100-200**	**200-500**	**500+**
Post x High Limit_Median	0.519*** (0.009)	121.5*** (6.0)	0.291*** (0.023)	0.394*** (0.014)	0.535*** (0.023)	98.9*** (16.9)	121.0*** (8.9)	165.6*** (13.0)
Observations	588,126	530,526	137,973	254,931	150,343	124,116	230,260	135,656
Credit Card User FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.569	0.136	0.497	0.536	0.603	0.132	0.135	0.145

Notes: Standard errors clustered at the credit card user level are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.10

Table A5: DiD Results for PCC Installments with Control Variables

	(1) ln_inst			
Post x High Limit_Median	0.519***	0.422***	0.518***	0.470***
	(0.009)	(0.010)	(0.009)	(0.009)
ln_hhi			-9.930***	-2.041***
			(0.085)	(0.111)
post			1.153***	0.389***
			(0.006)	(0.010)
ln_disp_inc		1.358***		0.684***
		(0.054)		(0.007)
Observations	588,126	588,126	588,126	588,126
Credit Card User FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	No	No
R-squared	0.569	0.570	0.561	0.569

Notes: Standard errors clustered at the credit card user level are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.10

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24-023 **Oguzhan Cepni, Selçuk Gül, Abdullah Kazdal, and Muhammed Hasan Yılmaz:** Energy Supply and Industrial Outcomes: A Quasi-Experimental Evidence from Recent Natural Gas Outage.

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