CENTER FOR
ECONOMIC
BEHAVIOR &
INEQUALITY

CEBI WORKING PAPER SERIES

Working Paper 07/22

WHAT DRIVES THE DEMAND FOR HIGH-COST CONSUMPTION LOANS?

Emil Toft Hansen

ISSN 2596-447X

CEBI
Department of Economics
University of Copenhagen
www.cebi.ku.dk

What drives the demand for high-cost consumption loans? *

Emil Toft Hansen[†]

June 2022

Abstract

This paper utilizes high-quality transaction data from the largest bank in Denmark to study what drives the demand for high-cost consumption loans. I investigate the extent to which adverse events drive loan demand, or if it is more likely to be explained by borrowers' personality traits. I find no evidence suggesting that borrowers suffer expenditure, health or social shocks at the time of borrowing. There are indications that some borrowers suffer income shocks, but the magnitude is too modest for this to be an important determinant of aggregate loan demand. Instead, I find evidence pointing towards a dominant role for borrowers' personality traits in explaining loan demand. Using paycheck sensitivity as a proxy, I show that high-cost borrowers appear to be significantly more present-biased than other consumers. I also document that high-cost borrowers are more prone to temptation spending as they spend much more on gambling than other consumers, both leading up to and when borrowing for the first time. Further, I find that high-cost borrowers persistently spend more than they earn and that this gap widens further as they approach the time of their first high-cost loan. Lastly, I document a large increase in non-essential spending around the time of borrowing. Taken together, the results indicate that high-cost borrowers have self-control problems and that high-cost loans are likely used to finance impulse spending or function as a way to prolong a credit-financed spell of overconsumption.

Keywords: High-Cost Credit, Payday Loans, Consumption Loans, Household Finance, Consumer Behaviour, Transaction Data

JEL Codes: D12, D14, D15, D18, G51

*Acknowledgments: I thank Asger Lau Andersen, Niels Johannesen, Adam Sheridan, Tue Lehn-Schiøler, Peter Lundgaard Rosendahl, Louise Aggerstrøm Hansen, Joachim Kahr Rasmussen, Ida Lykke Kristiansen and Kristian Olesen Larsen for helpful comments and suggestions. This research was facilitated by Emil Toft Hansen's Industrial PhD project, jointly financed by Danske Bank and Innovation Fund Denmark and further supported by Center for Economic Behavior and Inequality (CEBI), which is funded by the Danish National Research Foundation. More details on Innovation Fund Denmark's Industrial PhD programme are available at https://innovationsfonden.dk/en/programmes/industrial-researcher. Support from Danske Bank, Innovation Fund Denmark, and Center for Economic Behavior and Inequality (CEBI) is gratefully acknowledged. All individual data used in this analysis has been anonymised and no single customer can be traced in the data. All data processing has been conducted by authorized Danske Bank personnel, following the bank's strict data privacy guidelines. Danske Bank did not review the conclusions of this paper before circulation and the opinions expressed are those of the author alone and do not represent the views of Danske Bank.

[†]Danske Bank, University of Copenhagen and CEBI, email: eth@econ.ku.dk

1 Introduction

High-cost consumption loans, often named payday loans, are controversial and subject to much debate. The typical cost of a payday loan annualizes to as much as 1,000% (Bhutta et al., 2015). With such high interest rates, these loans are often accused of doing more harm than good. Critics often argue that high-cost consumption loans are predatory, that they exploit consumers with self-control problems, and that they ultimately lead consumers to spend more in the short run than they would like to in the long run. Proponents on the other hand argue that from a neoclassical point of view, the supply of such loans cannot be bad for consumers. If consumers decide to borrow at high interest rates, it must be because it is beneficial for them to do so. These views can be seen as a disagreement about why consumers demand high-cost credit. Do consumers, in line with the proponent view, borrow because of circumstances, e.g., because they suffer shocks to their income or health? Or do they, in line with the opponent view, borrow due to inherent personality traits, e.g., because they have self-control problems?

I explore this question by leveraging high-quality transaction data from the largest bank in Denmark, which serves more than one quarter of the Danish adult population. I construct a high-frequency individual-level dataset with detailed information on income, spending, liquidity, and importantly, use of high-cost credit. I exploit text string information from inflowing transactions to identify the set of counter accounts that high-cost credit companies use to transfer loan proceeds to borrowers. Identifying the use of high-cost consumption loans through bank transaction data has several advantages, especially in a Danish context. Firstly, in the Danish setting, where loans are only available online, the transaction data is likely to contain the full universe of high-cost credit companies. This contrasts with other studies, which use data from a single lender (e.g., Agarwal et al., 2009; Skiba and Tobacman, 2008), or which use transaction data in a context where store-front lenders are also prevalent (e.g., Baugh, 2016). Secondly, besides allowing identification of high-cost loans, the transaction data also enables me to get a close to complete overview of consumers' financial behaviour. This facilitates a more thorough analysis of why consumers use high-cost credit. For instance, it allows me to investigate not only whether liquidity is low when consumers borrow, but also *why* liquidity is low.

To understand better what drives the demand for high-cost credit, I first characterize the typical high-cost borrower. I characterize high-cost borrowers both with respect to traditional demographic and socio-economic measures, such as age, gender, and employment status, and also provide a comprehensive overview of high-cost borrowers' financial situation, including detailed information on how much they spend, earn, and save. I further develop two indicators for the borrowers' personality traits. Firstly, motivated by prior research that has shown a connection between present-bias, spending and borrowing, I construct a measure of present-bias.[1] Specifically, I implement the paycheck sensitivity methodology developed in Kuchler and Pagel (2021) to get a group-wide indicator of present-bias. Secondly, I exploit the fact that *gambling*, which is commonly considered

[1] A non-exhaustive list of studies documenting either a theoretical or empirical relation between present-bias and spending/borrowing includes Laibson, 1997; Skiba and Tobacman, 2008; Meier and Sprenger, 2010; Gathergood, 2012; Laibson et al., 2018; Kuchler and Pagel, 2021.

as a temptation good (Evans and Popova, 2017), is a separate and identifiable expenditure category in the transaction data, and use gambling expenditures as an indicator of individuals' proneness to temptation spending.

Following the characterization of high-cost borrowers, I utilize the panel structure of the data to explore the dynamic patterns in income, expenditures and various shock measures around the time of the high-cost borrowers' first high-cost loan. Specifically, I define a balanced sample of borrowers that I can observe 12 months before and six months after their first high-cost loan. I then study the evolution in total expenditures and total income as well as subcategories of both. To investigate the extent to which borrowing is driven by adverse circumstances, I define a range of binary shock indicators. I define an expenditure shock as a month where an individual has unusually large expenditures on car mechanics, dentists, or other health-related expenditures. I define an income shock as a month where an individual's total income is unusually low. I define two proxies for health shocks: one is defined as months where an individual receives sickness benefits, conditional on not receiving sickness benefits in the preceding three months. Another is defined as months where an individual has unusually large expenditures in drugstores. Lastly, I use address changes to proxy for social events and define a social shock as a month where an individual changes address.

I make a number of novel findings. Firstly, I document that high-cost borrowers persistently spend more than they earn. I find high-cost borrowers to have substantially higher expenditures than income already 12 months before their first use of high-cost credit. As they approach their first high-cost loan event, the gap between expenditures and income widens further. Secondly, I find that high-cost borrowers tend to spend much more on gambling than other consumers, with the top decile gambling for 14,000 DKK each month on average. Thirdly, I show that high-cost borrowers as a group appear to be more present-biased than other consumers, also after controlling for age, gender, income, and liquidity. Specifically, I find that high-cost borrowers have paycheck sensitivities that are almost double that of normal consumers. Lastly, I find only limited evidence suggesting that high-cost borrowers experience shocks around the time of their first high-cost loan event. There are no signs that borrowers suffer expenditure, health or social shocks, and while I do find indications that some borrowers suffer income shocks, the numbers are too small for this to be an important driver of aggregate loan demand.

Taken together, these findings indicate that circumstances, i.e., borrowers being hit by adverse events such as car breakdowns, job losses or social shocks, are an unlikely driver of high-cost borrowing. Instead, the evidence suggests a dominant role for borrowers' personality traits in explaining loan demand. Specifically, the findings indicate that high-cost borrowers have self-control problems in the form of large degrees of present-bias and a proneness towards temptation spending. These are two traits that have been associated with excessive short run consumption, both theoretically (Laibson, 1997; Gul and Pesendorfer, 2001; Harris and Laibson, 2013; Laibson et al., 2018) and empirically (Meier and Sprenger, 2010; Gathergood, 2012; Kuchler and Pagel, 2021). Combined with the fact that I also observe a large increase in non-essential spending at the time of borrowing, it seems likely that high-cost loans are used primarily to finance impulse spending or function as a way to prolong a credit-financed spell of overconsumption.

These findings contribute to a broad literature studying the use of high-cost credit. The paper that is most related to the present study in terms of motivation is Skiba and Tobacman (2008), who also ask what drives the demand for high-cost credit. They take a more structural approach, however, and estimate a dynamic programming model featuring liquidity constrained consumers who experience income and expenditure shocks. They calibrate the model to observed payday borrowing behaviour and find that borrowing behaviour is better explained by partially naïve consumers with quasi-hyperbolic time preferences than by exponentially discounting consumers who experience income and expenditure shocks. This aligns with my empirical findings of limited circumstance-driven borrowing, but clear signs of borrowers having relatively high degrees of present-bias.

A large part of the literature studying high-cost credit consists of reduced-form empirical investigations of how access to high-cost credit affects consumers. Notable examples include Melzer, 2011; Carrell and Zinman, 2014; Baugh, 2016; Melzer, 2018; Gathergood et al., 2018; Skiba and Tobacman, 2019 who all find negative effects; Zinman, 2008; Morse, 2011; Zaki, 2016; Dobridge, 2016 who generally find positive effects and Bhutta et al., 2015; Bhutta et al., 2016 who find null-effects. As indicated, the results are mixed, although with an overweight towards finding negative effects. My findings help to rationalize these negative reduced-form estimates: If most of borrowing is driven by behavioural biases, then it is also likely that high-cost borrowing leads to (increased) financial hardship.

The present paper also relates to studies that characterize the circumstances under which consumers turn to high-cost credit, e.g., Bhutta et al. (2015) and Carvalho et al. (2019). Bhutta et al. (2015) find that high-cost borrowers turn to high-cost credit when they have exhausted all other credit options. Further, they show that borrowers have low liquidity and poor credit scores several years before they first apply for a high-cost loan. Similarly, Carvalho et al. (2019) find that high-cost borrowers in Iceland have very low liquidity just before they borrow. I re-confirm these findings of (long-run) low levels of liquidity, but also provide an explanation for why liquidity is low: High-cost borrowers appear to be persistently consuming beyond their means, a behaviour that is likely explained by low levels of self-control.

Another set of related papers study the intersection between consumption and payday borrowing (Baugh, 2016; Dobridge, 2016; Carvalho et al., 2019). The main focus of these studies is not to determine what drives the demand for high-cost credit, but rather to investigate the causal effect of loan access on consumption (Baugh, 2016; Dobridge, 2016), or to study the decision-making ability of high-cost borrowers (Carvalho et al., 2019). Still, my findings are in line with the results of both Baugh (2016), who finds that payday loans are used to finance gambling expenditures, and Carvalho et al. (2019), who find large expenditure increases for both non-essentials and total spending around loan take-out.

Lastly, the present study also relates to papers that investigate the broader connection between behavioural biases and spending behaviour. One strain of this literature explores theoretically how present-bias affects consumption patterns and finds that present-bias leads to higher consumption and more borrowing (Laibson, 1997; Harris and Laibson, 2013; Laibson et al., 2018). A number of empirical applications bring these predictions to the data and show how present-bias is associated with more credit-card borrowing (Meier and Sprenger, 2010), over-indebtedness (Gathergood, 2012), and slow debt repayment (Kuchler and Pagel, 2021). I contribute to this literature by documenting a connection between present-bias, overspending and high-cost borrowing.

The insight that the main part of high-cost borrowing is linked to borrowers' personality traits has important policy implications. If consumers borrow because of behavioural biases and self-control problems, then it is likely that credit access actually hurts consumers by allowing them to consume more here and now than what they would optimally like to in the long run (Laibson, 1997). However, many high-cost borrowers appear to be on an unsustainable consumption path long before they start to use high-cost credit, pointing towards a more fundamental challenge of behaviourally biased consumers making suboptimal decisions. Further, there are at least some consumers who borrow to smooth over (income) shocks. This indicates that restricting loan access is at most a second-best solution. Instead, there is a need for more ambitious interventions that can help alleviate behavioural biases among consumers, e.g., by improving financial literacy or by providing tools that help consumers monitor their expenditures and cope with self-control problems.

The rest of the paper is organized as follows. In section 2, I describe the market for high-cost credit in Denmark. In section 3, I describe the data and explain the sample selection. In section 4, I go through the empirical strategy. In sections 5 and 6, I present the empirical results. Finally, in section 7, I sum up and conclude.

2 High-cost consumption loans in Denmark

During the last decade, the Danish market for high-cost consumption loans has expanded rapidly, going from around 20,000 loans in 2010 (DCCA, 2015) to more than 350,000 loans in 2018 (DR, 2019). High-cost consumption loans (in Denmark, popularly known as "kviklån"/"quick loans") are small and often not larger than 4,000 DKK. They are considered as quick and easy to access, but also very expensive with monthly interest rates around 20% (DCCA, 2015). Customers apply for loans online and if the application is approved, loan proceeds are transferred to borrowers' bank accounts within hours or even minutes. These features have made high-cost consumption loans subject to much controversy and political debate, and the market has been regulated on multiple occasions during the last 10 years. Despite this, high-cost consumption loans are in a Danish context an understudied phenomenon. There are no systematic records of the use of high-cost credit and while most Danes will be familiar with the concept of "kviklån", there does not exist an official definition of what a "kviklån" actually is. The best candidate for a delineation principle comes from a report from 2015 from the *Danish Competition and Consumer Authority*. In this report, "kviklån" is defined as *"unsecured consumer credit with a maturity of maximum three months"* (DCCA, 2015). I follow this definition and identify 25 high-cost credit companies, that have been active in the market for high-cost consumption loans at some point in the period 2014-2019[2]. Although the delineation criteria focuses on maturity, the identified companies are all characterized

[2] I go further into detail on this identification process in section 3.

by offering consumer credit with very high interest rates. Most companies offered loans with monthly interest rates around 15-20%, which translates into compounded annual percentages rates (APRs) of up to 800%. A few companies had lower interest rates and instead charged substantial loan establishment fees. Loan amounts were generally small, with the majority of companies offering loans ranging from 0-10000 DKK and a few companies offering loans up to 25,000 DKK.[3]

Before 2017, the typical loan had a maturity around 1-45 days (DCCA, 2015). This changed in January 2017 due to a new regulation, that introduced a 48 hour "cool-down" period for unsecured loans with a maturity below three months. This meant that borrowers had to wait 48 hours before they would receive the money. However, only a few credit companies followed this new regulation. Instead, most companies circumvented it by modifying their loan products into longer maturity products. The most common loan product type to emerge was a loan without a due date, one that could in principle go on for years as long as borrowers paid a monthly minimum payment corresponding to the monthly interest.

While high-cost credit attracts substantial attention, it still only accounts for a fraction of total consumer credit. According to official national statistics, unsecured consumer credit supplied by the non-bank sector (which high-cost credit is a part of) accounts for less than 5% of total consumer credit[4]. This reflects that high-cost credit is generally considered a last resort of consumer credit. More popular alternatives include overdraft facilities and credit cards supplied by the bank-sector and larger and less expensive consumption loans supplied by other non-bank credit companies, which I term as "midtier credit companies".

Lastly, while outside the time window I consider in my analysis, it is worth mentioning that the market was further regulated in July 2020, where a cap of 35% on the compounded APR and a cap of 100% on the total yearly loan costs were introduced. This appears to have effectively closed the market for high-cost credit in Denmark as less than a handful of companies still actively offer credit today and this at a cost much lower than before.

3 Data, measurement and sample selection

I extract information on high-cost consumption loans, expenditures, income, and liquidity using transaction-level data from the largest bank in Denmark, Danske Bank. Danske Bank serves more than one quarter of the Danish adult population and the customer base is generally representative of the Danish population with respect to age, gender, income, and other characteristics.[5] I have comprehensive data on spending, income and liquidity for the years 2016-2019 and on high-cost consumption loans for 2014-2019. While most measures, such as expenditures and liquidity are available on a very high frequency, e.g., on a daily level, other measures such as income are only meaningful on a monthly frequency. To facilitate comparison, I therefore aggregate data to the monthly frequency.

[3] In appendix B, I provide a couple of snapshots documenting the concrete loan offers.

[4] These figures apply for Q1 2019, cf. Statistikbanken.dk, MPK30

[5] I present summary stats that compares the Danske Bank customer sample to the Danish population in appendix table C.1.

3.1 Data and measurement

Spending data

I rely on the bank's internal classifier system to categorize outgoing transactions. I define *total expenditures* as the sum of all card, cash, mobile wallet,[6] and bill spending. Note that I include the transfer part of mobile wallet transactions (i.e., transfers to friends and family) as part of total expenditures. The only categories I exclude are taxes and savings/investments. This means that I include financial services, such as debt services, in total expenditures to capture that financial obligations might impose a significant burden on high-cost borrowers' budgets.

I split total expenditures into seven subcategories. First, I define *cash withdrawals*, *transfers*,[7] and *financial services* as three separate categories. I also define *gambling* as a separate category, as this is a sharply delimited consumption good often considered as a temptation good.[8] I split the remaining part of total expenditures into *essentials* and *non-essentials* based on engel-curves following Jørring (2020). Specifically, I define expenditure categories with an upwards sloping engel-curve as non-essentials and expenditure categories with a downwards sloping engel-curve as essentials. Two subcategories er undefinable using this methodology: *Insurances* and *fees & fines*. I add these to a residual category, along with unlabelled card and bill spending. All expenditure categories, engel-curves, and a more detailed description of this procedure are found in appendix D.

Income data

Income data is based on inflows into customers' bank accounts. I rely on a ML-based classifier developed internally in the bank to categorize inflowing transactions as salaries, government transfers, pension and so forth. I define *total income* as the sum of all salaries, government benefits, and pension plus cash deposits and MobilePay transfers, countering that I include cash withdrawals and MobilePay transfers on the expenditure side. I also investigate subcategories of total income separately, focusing on *salary income*, *unemployment benefits* (covering both cash benefits and unemployment benefits), *pension income*, *student benefits* and *MobilePay transfers*. Further, I also use sickness benefits as a proxy for health shocks (explained in detail in section 4).

Balance sheet data

For customer balances, I focus on all customer accounts that are liquid in the sense that the customer can easily access funds on these accounts. This includes transaction accounts, savings accounts and loan product accounts, but disregards mortgage and pension accounts. I have two balance sheet concepts: *Actual account balances* and *available liquidity*, where the difference between the two is any unused credit the customer might have at the bank. For both measures, I average over daily levels to get a monthly measure.

[6] Mobile wallet transactions consist mainly of MobilePay (which is the market dominating service in Denmark for transferring money to individuals) and to lesser degree of Apple Pay and Google Pay services.

[7] Transfers consist mainly of MobilePay transfers and to lesser extent of traditional money transfer services such as Western Union.

[8] Since good categorization happens on a store level, it is not possible to separate other typical temptation goods such as alcohol or tobacco from everyday grocery spending.

Demographic data and proxies for parental support and midtier credit use

I extract information on customer age and gender from general customer registers. I also extract monthly address information and use this to develop a monthly dummy for whether an individual has changed address.

I use the net amount of money transferred to and from accounts belonging to individuals' parents to construct a proxy for parental financial support. I find the accounts of the parents by searching for inflowing bank transfers where the text field contains either "fra mor" or "fra far", which is Danish for "from mom" and "from dad". I then for each individual delimit the set of counter accounts that are found to transfer money with these text tags and sum the net amount of transfers between the individual and these counter accounts. I interpret this as a proxy for parental support. Note that I am likely to underestimate the level of parental support for at least two reasons: 1) Some parents will not label their transfers with "fra mor" or "fra far" and 2) I only include bank transfers in this proxy and not Mobilepay transfers as this does not carry any useful text field information in my data. Due to this, this measure should only be seen as a proxy that allows relative comparison of parental financial support between different groups.

I also construct a proxy for high-cost borrowers' use of "midtier credit companies". As mentioned in section 2, midtier credit companies are non-bank companies that also offer consumer credit. They typically offered credit with an annual interest rate somewhere around 10-50%, which is substantially higher than the average interest rate charged by traditional Danish banks, but still much lower than the interest rate charged by the high-cost credit companies. It is unfortunately beyond the scope of this study to cover the full universe of midtier credit companies (as I do for high-cost companies). Instead, I focus on three of the most common midtier credit companies, namely Santander Consumer Bank, Ekspress Bank and Resurs Bank, and sum all transfers that individuals receive from these companies. As for the parental support proxy, this means that one should not attach too much weight to the absolute levels of this measure, but instead focus on relative differences between groups.

High-cost consumption loan data

The transaction data contain all inflowing transfers to bank customers' bank accounts. The challenge in identifying high-cost consumption loans is therefore a challenge of determining which inflowing transfers are transfers of loan proceeds from high-cost credit companies. The first step in this process is to delineate the set of high-cost credit companies. My starting point for doing this is the 2015 report from the *Danish Competition and Consumer Authorities*, mentioned in section 2 (DCCA, 2015). I first directly include the seven companies that are mentioned in this report. I then use the report's definition of high-cost consumption loans, and search online loan comparison websites for credit companies offering consumer credit with a maximum maturity of four months.[9]

[9]Note that I set the maturity limit to four instead of three months, which was otherwise the maturity threshold defined in the 2015-report. This is to accommodate for the effect of the 48-hour cool-down period introduced in 2017, which prompted many credit

I strive to be as stringent as possible when searching online for high-cost credit suppliers. I begin by searching on Google for “kviklån sammenligning” (”quick-loan comparison” in Danish).[10] I restrain myself to only use the first ”Google results” page and only consider comparison websites that clearly indicate the maturity of the loan. I list the comparison websites I end up using in appendix A.[11] From these websites, I extract all companies that offer a loan with a maturity below four months.

I then use text field analysis to identify the high-cost credit companies in the transaction data. Specifically, I extract all inflowing transactions in the period 2014-2019 where (part of) the text string accompanying the transaction matches (part of) the name of a high-cost credit company. This isolates a large number of transactions, where some are clearly genuine loan proceeds transfers while others are ”inter-customer” transfers, i.e., personal customers transferring money to other personal customers and labelling the transaction with the name of a credit company. For each transaction, I extract the counter account and the name of the company that I found in the text string of the transaction. This provides a gross list of companies and their potential counter accounts. I filter out inter-customer transfers by requiring for each counter account that at least four unique customers have received money from it. This leaves me with a manageable number of counter accounts that I manually inspect to determine whether they belong to a high-cost credit company or not.

For some companies I do not find any common counter accounts based on the text field analysis of inflowing transactions. I do, however, find some common counter accounts for negative transactions, i.e., personal customers who repay loans and write the name of the credit company in the transaction’s text field. I use this in a “backwards induction” framework and systematically isolate customers who have made payments to an unidentified company, one company at a time. I then redo the process from above, restricting to counter accounts that at least four unique bank customers have received money from and manually check whether they belong to a high-cost credit company.

As a last step to ensure that I capture the full universe of high-cost credit companies, I utilize the fact that high-cost borrowers tend to borrow from many different companies. This means that if any companies are missing from the initial set of companies that I found on the comparison websites, then they are likely to show up in the transactions of the high-cost borrowers. I therefore go through all the counter accounts that this preliminary set of identified high-cost borrowers frequently receive money from, and check whether the transactions transferred from these counter accounts look similar to the transactions I have already identified as high-cost loan transactions. By doing this, I discover two additional credit companies which I did not find when I searched the loan comparison websites. I include these two companies in my final list of credit companies and identify their counter accounts as well.

In the end, I identify the counter accounts of 25 high-cost credit companies. As for the other data elements, I collapse to a monthly frequency and define monthly high-cost borrowing as the sum of all incoming transactions

companies to extend the maturity of their loan products beyond three months.

[10] I have done this exercise two times. First in November 2018 and again in November 2019.

[11] In appendix B, I provide a snapshot of one of these comparison websites.

from these counter accounts. I provide a brief overview of the amount of high-cost borrowing in table 1. On average, borrowers borrow for approximately 5,400 DKK in the first month that they borrow. The distribution is relatively right skewed, with a median of 4,000 DKK and a 95 percentile of 15,000 DKK. The total amount of 5,400 DKK is based on 1.5 independent loans, with an average size of approximately 3,700 DKK. Once started, most borrowers continue to borrow. Letting month 0 denote the month that borrowers borrow for the first time, I find that borrowers borrow for an additional 9,000 DKK in the following six months, meaning that total average borrowing from month 0 to month 6 is approximately 14,000 DKK. Again, the distribution is right skewed, with the median borrower borrowing for 8,500 DKK, while the 95 percentile borrows for as much as 45,000 DKK over these seven months. I also count the number of months where borrowers are borrowing over this seven-month period. I find that at least half borrow in two months or more, 75% borrow in four out of seven months and the 95 percentile borrows in six out of seven months. Lastly, I investigate how many different firms high-cost borrowers borrow from over the seven-month period. I find that borrowers on average use two different firms, but the distribution is again very right skewed as the median only uses one firm and the 95 percentile uses as many as six different firms.[12]

Table 1: Descriptive statistics of high-cost consumptions loan data

	Average	p5	p25	p50	p75	p95
Amount borrowed, month 0	5390.3	1000	2500	4000	6000	15000
Number of loans, month 0	1.5	1	1	1	2	3
Average loan amount, month 0	3674.2	500	1600	3000	4000	10000
Amount borrowed, month 0-6	14375.4	2000	4000	8607	18000	45769
Number of loans, month 0-6	4.8	1	1	3	6	16
Number of months with borrowing, month 0-6	2.6	1	1	2	4	6
Number of unique companies, month 0-6	2.0	1	1	1	2	6

The table contains information on the monthly amounts borrowed, number of loans and average loan size. Month 0 denotes the month where high-cost borrowers borrow for the first time. Month 0-6 denote the seven month period, going from month 0 and six months forwards.

3.2 Sample selection

The aim of my sample selection process is to delimit a sample of individuals, who 1) are active bank customers, meaning that they are likely to use Danske Bank as their primary bank and hence conduct the majority of their economic activities through this bank; 2) borrowed from a high-cost credit company for the first time in the period from 2016 to 2019; 3) who appear in the data for at least 12 months before and six months after their first high-cost borrowing event. To this end, I start by defining a baseline sample of individuals who have received money from a high-cost loan company at least once during the period 2014-2019. I then exclude everyone who received money from a high-cost credit company in 2014-2015, and assume for everyone else that the loan they take in 2016-2019 is their first high-cost loan.[13] Next, I define an individual to be an active customer in a given

[12]Note that firm refer to parent company, meaning that borrowers who have borrowed from just one "firm" can in principle have borrowed from multiple credit companies within the same parent company.

[13]There are two potential reasons for why I might still not be observing their first loan. First, individuals might have borrowed from a high-cost credit company before 2014. I believe this to be unlikely as the market for high-cost credit was relatively small before 2014 (DCCA, 2015). Second, individuals might have borrowed through another bank. Again, I do not believe this to be a

month if said individual in this month had at least one outgoing transaction of more than 50 DKK and was registered to have her main transaction account ("nemkonto") at Danske Bank. I then restrict my sample to all individuals who are active customers for at least 12 months before and six months after their first high-cost borrowing event. Finally, I drop individuals whose first high-cost loan is below 100 DKK or above 500,000 DKK. This leaves me with a balanced[14] sample of approximately 12,000 individuals, who borrow from a high-cost credit company for the first time in the period 2017-2019[15] and where I observe them at least 12 months before and six months after their first high-cost loan. Note that I observe some individuals significantly longer before or after, depending on data availability and the timing of their first high-cost borrowing event. Appendix figure C.1 shows the number of individuals in my sample by event time.

4 Empirical strategy

Static descriptive analysis

I first characterize the high-cost borrowers. I consider both a number of traditional demographic and socio-economic indicators such as age, gender, income and employment status, and also more elaborate "behavioural indicators" such as degree of present-bias, financial distress and temptation spending. The two latter are proxied using overdraft reminders and gambling expenditures. For degree of present-bias, I follow Kuchler and Pagel (2021), and use paycheck sensitivity as a measure of present-bias. More concretely, I investigate how much consumers' spending on short-run consumables[16] increase in pay weeks (i.e., weeks where they receive a paycheck) relative to normal weeks. To avoid that results are driven by liquidity constraints, I restrict to weeks where beginning-of-week liquidity is at least 1,000 DKK. Lastly, to avoid that inflow of high-cost loans influences the estimation, I use only observations going up to 30 days before the first high-cost loan event. I provide more detail in appendix E, where I also present robustness results that vary the definition of short-run consumables, the threshold of the liquidity constraint, and the sample period considered.

Comparison groups

Many of the measures considered in the static analysis are most meaningful when evaluated relative to some benchmark. I therefore create three comparison groups, which are all made by matching each individual in my main sample of high-cost borrowers with a comparison person. For each comparison person, I define an artificial "first high-cost loan date" equal to the actual "first high-cost loan date" of the high-cost borrower they are matched with. This enables me to also evaluate the comparison groups by event time and ensures that I have the same underlying seasonality patterns in all groups. I also require that I can follow each comparison person

major concern, as most credit companies only transfer loan funds to borrowers' "nemkonto" and I require that individuals have their "nemkonto" at Danske Bank at least 12 months before their first high-cost borrowing event.

[14] The sample is only strictly balanced in the 19 months window constituted by the 12 months before and six months after first high-loan event.

[15] Due to my requirement that individuals must appear in the data for at least 12 months before first high-cost loan event, I am effectively dropping individuals who borrow for the first time in 2016 as I haven't got data on spending and income before 2016.

[16] Short-run consumables are defined as *Food and daily purchases*, *Entertainment away from home*, *Restaurants and bars* and *gambling*.

for at least 12 months before and six months after the (artificial) first high-cost loan date.

The first comparison group is a simple random sample of bank customers. I simply match each high-cost borrower with a random bank customer, where the only requirement is that I can follow the comparison person 12 months before and six months after the first high-cost loan date of the matched high-cost borrower. I use this comparison group to assess how the high-cost borrowers compare to the general (customer) population. The second comparison group matches the high-cost borrowers on age and gender. Specifically, I match each high-cost borrower with a comparison person of the same gender (male/female) who is furthermore born in the same year-month. I use this comparison group to get a sense of how the high-cost borrowers compare to a group of individuals who are at the same stage in their lives, which is likely to be important for both the level and composition of income and expenditures. Lastly, I create a comparison group that is not only matched on age and gender, but also on income and liquidity. I again match on gender (male/female) and birth year-month, and then match to the person who is closest in terms of income and liquidity.[17]

Dynamic analysis

After having characterized the high-cost borrowers, I move to dynamic analyses of high-cost borrowers' income and expenditures around the time of their first high-cost loan event. Specifically, I investigate how average total expenditures and average total income evolve in the 12 months leading up to and the six months following the first high-cost loan event. I also consider subcategories of both to better understand what is underlying the observed patterns.

I also present estimates of the changes in total expenditures, total income and subcategories of both from month -1 to month 0. I use these changes as a measure of what loan proceeds are used to finance. Of course, I cannot say with certainty that loan proceeds are only used to finance expenses in the same month as individuals borrow. It might well be that part of loan proceeds are used to cover past or future expenses. Therefore, my focus in these analyses is on the relative difference between different components, i.e., how much larger or smaller is the change in total expenditures compared to the change in total income.

A key focus in this paper is to study whether high-cost borrowers appear to be suffering from various kinds of shocks, e.g., shocks to their income, expenditure shocks or shocks to their health or social life around the time when they borrow. To assess whether this is the case, I construct a range of binary shock indicators. I follow Andersen et al. (2020) and define an expenditure shock as a situation where payments to car mechanics, dentists or other health providers exceed DKK 2,500 in a given month.[18] I also draw inspiration from the definition of income shocks (job losses) in Andersen et al. (2020) to define an income shock as a situation where total income in month t is lower than 50% of average total income in the preceding three months, i.e., month t-1

[17]More precisely, I match on average income and average liquidity over month -12 to -1. I calculate "total distance" as the sum of the absolute difference in income and liquidity, giving the difference in income a weight of two to account for that income is a flow variable while liquidity is a stock variable. More formally, "total distance" is defined as: $total\ distance = 2 * abs(income\ distance) + abs(liquidity\ distance)$. In the end, the median differences in income and liquidity between the high-cost borrowers and the matched comparison group are just 460 and 900 DKK.

[18]Andersen et al. (2020) use a 5,000 DKK threshold. I set my threshold to 2,500 DKK to reflect that I am studying a group of individuals with low income and liquidity. In the appendix, I also present evidence for alternative threshold levels (1,000 and 5,000 DKK).

to t-4.[19] Next, I define health shocks using sickness benefits payouts. Specifically, I define an individual to experience a health shock if she in month t receives sickness benefits conditional on not receiving sickness benefits in the preceding three months. However, as this measure will only capture sickness events for individuals with a relatively strong labor market attachment,[20] I define an alternative health shock indicator as months where expenditures at drugstores exceed 1,000 DKK. Finally, I proxy for social shocks (which can be both positive or negative) with address changes.

The dynamic patterns of expenditures, income and the described shock indicators are likely to be influenced by underlying seasonality and age effects. Seasonality effects arise from the fact that individuals are more likely to use high-cost credit in some months rather than others. As income and expenditures vary systematically over the year, this can potentially bias the results. Age effects come from the simple fact that borrowers get older in the time window I follow them. Given that high-cost borrowers are generally young, this can have a rather large effect on the estimated expenditure and income patterns. I address these concerns by estimating the following regression:

$$y_{it} = \beta_0 + \sum_{m=-35}^{35} \delta_m E_{im} + \beta_1^{'} agebin_i + \theta_t + \epsilon_{it} \tag{1}$$

Where y_{it} is the outcome of interest, e.g., total expenditures or a binary shock indicator, E_{im} is a set of 70 event time dummies, going from month -35 to month 35 (and letting month -1 function as the omitted category), $agebin_i$ is a vector consisting of 11 five-year age bins that capture age effects, and θ_t is time fixed effects, specifically month and year fixed effects. When I present results by event time (as I for instance do in figure 1), I present them as predicted values, fixing all other variables than the event time dummies at sample averages.[21] This allows me to present the dynamics of the dependent variable around the time of the event in levels instead of relative differences. In the main text, I only show estimates for event time -12 to 6 where the sample is balanced. In the appendix, I also include estimates going further back and forth, but these should be interpreted with caution, as the results might be partly driven by selection effects.

5 What characterizes the high-cost borrowers?

I present a range of demographic, socio-economic and behavioural indicators in table 2. All indicators are measured exactly one year before borrowers borrow for the first time. The only exception is the paycheck sensitivity indicator, which is estimated using all observations available up until one month before the first high-cost loan event. Column (2) presents estimates for the high-cost borrowers and columns (3-5) present estimates for the three comparison groups.

[19] Again, I use this threshold as my baseline level in the main text, and present evidence using alternative threshold levels (25% and 75%) in the appendix.

[20] Eligibility to sickness benefits is contingent on labor market participation.

[21] Specifically, I calculate the sample averages of all covariates except the event time dummies. I then calculate the sum product of the covariate sample averages and the corresponding regression coefficient estimates. Lastly, to get the final predicted value for a given event time, I add the estimated coefficient of said event time to this sum product.

The top panel shows basic demographic measures. I find that high-cost borrowers are substantially younger than the average bank customer (column five). High-cost borrowers are on average just 34.6 years old and almost 50% are below 30 years old. I also find a slight underrepresentation of female borrowers, but the difference is relatively modest. For the subset of women, I find that high-cost borrowers are slightly more likely to be mothers than the average bank customer with the same age and gender characteristics (column four), but not more likely than the group which is also matched on income and liquidity (column three).

The next panel shows socio-economic indicators. I find that the high-cost borrowers have relatively low labour market participation, both compared to the random sample and especially when taking their age and gender composition into account. This is also reflected in the high share of borrowers receiving unemployment benefits, which is double that of the age and gender matched comparison group. The high-cost borrowers are also less likely to be studying, proxied for by the share receiving student grants, and on the other hand more likely to receive sickness benefits. In line with the lower share of students among the high-cost borrowers, I also find that they are less likely to live in urban areas and more likely to live in rural areas, especially when compared to the age and gender matched comparison group.

I next zoom in on their income, liquidity and spending. I first show that high-cost borrowers have relatively low income, both compared to the random sample and when taking their age and gender composition into account. Next, I find that the high-cost borrowers hold basically zero wealth on their bank accounts already one year before they borrow for the first time. One could suspect that this is simply a reflection of their age profile, but this is not the case, as demonstrated by the relatively high levels of wealth held by the age-gender matched comparison group. I go from account balances to disposable liquidity by including all credit available within the bank. I find the high-cost borrowers' available liquidity to be slightly higher than their account balances, but it is still very low. On average, high-cost borrowers have less than a month's worth of expenses in available liquidity. It is of course not a surprise to find a group of individuals that are selected on their credit demand to have low liquidity. But it is rather striking to see that their liquidity levels are so low already a year before they start using high-cost credit. While table 2 only shows average levels, I present the full distribution of liquidity in appendix table C.2. It is heavily right skewed, with the average being close to the 80 percentile, indicating that it is the vast majority of the high-cost borrowers that have very low liquidity already a year before their first high-cost loan event.

In light of their low levels of income and liquidity, it is remarkable to see that the high-cost borrowers have expenditures that are on average close to the expenditures of the comparison group in column four and substantially above the comparison group in column three. This means that high-cost borrowers on average spend more than they earn with an expenditure to income ratio of almost 1.10. For the three comparison groups, this ratio is close to 1, with the age and gender matched group being the closest follower with an expenditure/income ratio of 1.01.

In the bottom panel, I explore a range of behavioural and other miscellaneous indicators. Firstly, using the Kuchler and Pagel (2021) measure of present-bias discussed in section 4, I find that high-cost borrowers demonstrate a larger tendency towards being present-biased than other consumers. The group-wide estimated paycheck sensitivity of the high-cost borrowers is close to 30% larger than the estimated sensitivity of the comparison group in column three and close to double compared to the comparison groups in column four and five. It is not surprising that the comparison group that is also matched on income and liquidity is relatively close to the high-cost borrowers in terms of paycheck sensitivity, given that present-bias is likely to lead consumers to low levels of liquidity. In this light, it seems plausible that this comparison group also suffers from some degree of present-bias albeit to a lower extent than the high-cost borrowers. Therefore, for this measure, it is probably most relevant to focus the comparison to the two comparison groups that are not matched on income and liquidity. As described in section 4, I implement the Kuchler and Pagel (2021) measure of present-bias using a broad definition of short-run consumables, a liquidity constraint threshold of 1,000 DKK and observations going up to 30 days before first high-cost loan event. In appendix table E.1, I show that the estimates presented here are robust to variations in all three dimensions. I find it especially interesting that altering the time horizon (i.e., using only observations from at least one year before the first high-cost loan event) does not change the estimates. This provides reassurance that the measure is really capturing stable inherent personality traits that do not change over time. Next, I use overdraft reminders as a proxy for financial distress, and find that high-cost borrowers are more likely than other consumers to be in a situation of financial distress. While it is expected that the high-cost borrowers receive more reminders than the comparison groups not matched on income and liquidity, it is somewhat surprising to see that they are also significantly more likely to receive reminders than the comparison group matched also on income and liquidity, as this can hardly be explained by financial conditions. One possible interpretation is that the high-cost borrowers are more likely to procrastinate or that they have lower financial abilities, which other studies have shown to be the case for users of high-cost credit (Carvalho et al., 2019).

I also study to what extent high-cost borrowers are supported financially by their parents as measured by the net amount of money transferred to and from the accounts of their parents. I find that high-cost borrowers are less likely to receive parental financial support relative to the comparison groups. A potential explanation of this finding is that the high-cost borrowers' parents have relatively few resources themselves, in line with the evidence of financial difficulties across generations documented in Kreiner et al. (2020). Finally, I also document that the high-cost borrowers are more likely than other consumers to borrow from midtier credit companies. This indicates that high-cost borrowers are credit financing part of their consumption already 12 months before they start using high-cost credit.

Table 2: Static characterization of the high-cost borrowers

	High-cost borrowers	Comparison groups matched on		
		Customer status, age, gender, income and liquidity	Customer status, age and gender	Customer status
Demographics				
Avg. age *(years)*	34.6	34.3	34.3	**48.1**
18-30 years old *(%)*	46.5	47.0	47.0	**20.7**
30-50 years old *(%)*	36.9	36.8	36.8	**32.1**
50+ years old *(%)*	16.6	16.1	16.2	**47.2**
Share female *(%)*	46.4	46.4	46.4	**51.9**
Share mothers *(%)*	19.2	19.6	**17.0**	**16.2**
Socio-economic indicators				
Receives labor income *(%)*	58.2	**60.9**	**70.5**	**62.2**
Receives unemployment benefits *(%)*	20.7	**18.8**	**10.3**	**9.4**
Receives pension income *(%)*	11.3	**10.0**	**8.2**	**28.4**
Receives student benefits *(%)*	16.6	**20.5**	**20.7**	**8.9**
Receives sickness benefits *(%)*	1.3	1.0	**0.7**	**0.8**
Living urban *(%)*	11.5	**15.3**	**18.4**	**14.9**
Living rural *(%)*	14.4	**13.1**	**12.0**	13.5
Household finances				
Total monthly income *(1000 DKK)*	15.8	15.6	**18.4**	**22.2**
Account balances *(1000 DKK)*	-0.8	**2.5**	**82.9**	**140.7**
Available liquidity incl. credit *(1000 DKK)*	13.1	12.9	**123.7**	**182.4**
Credit limits *(1000 DKK)*	13.8	**10.4**	40.7	**41.7**
Total monthly expenditures *(1000 DKK)*	17.3	**15.2**	18.6	**20.7**
Behavioural characteristics				
Pay-check sensitivity *(%)*	42.3	**32.8**	**22.6**	**21.4**
Parental financial support *(%)*	1.2	1.2	**2.5**	**0.2**
Midtier credit *(%)*	0.9	**0.2**	**0.1**	**0.1**
Received reminder *(%)*	7.0	**5.4**	**2.6**	**2.1**
Observations	12151	12151	12151	12151

The table reports descriptive statistics for the group of high-cost borrowers and the three comparison groups explained in section 4. All outcomes (except paycheck sensitivity, which is measured using all available data up until 30 days before first high-cost loan event, cf. appendix E) are measured 12 months before first high-cost loan event. Bold emphasis indicate that the difference to the high-cost borrowers is significant on a 0.01 level. *Are mothers* is a proxy for being a mother, based on receiving child benefits. In this time period, child benefits are only paid out to women, why this measure is only capturing the share of women being mothers. The five first socio-economic indicators are all binary indicators equal to 1 if an individual receives any positive amount of this income in a given month. Living urban is a proxy for living in a densely populated area. It is based on address data and the "Danish National Grid" where an address is said to be in an urban environment if there is at least 100,000 other addresses in the address' 10 km^2 grid and 5000 addresses in the address' 1 km^2 grid. Living rural is a proxy for living in a sparsely populated area and is equal to one if there is at maximum 5000 other addresses within an address' 10 km^2 grid. "Parental financial support" is a proxy for parental support equal to 1 if net parent transfers exceed 500 DKK in a given month. "Midtier-credit users" is a proxy for usage of midtier credit. It is too a binary indicator equal to 1 if borrowing from midtier credit companies exceeds 500 DKK in a given month. Both the parent financial support and the midtier credit proxy are further explained in section 4. Received reminder is a binary indicator of whether an individual received any kind of debt / overdraft reminder from the bank in a given month.

Expenditure shares

Above I documented that the high-cost borrowers spend around 2,000 DKK more per month than the comparison group matched on age, gender, income and liquidity, despite these two groups having equal levels of income and liquidity. I explore what underlies this difference in table 3, where I decompose total expenditures into subcategories. I find that high-cost borrowers and the comparison group spend similar amounts on *essentials*, although the high-cost borrowers spend slightly less on mortgages, indicating that they are less likely to be home owners. They also spend comparable amounts on *non-essentials*, both in total and for each subgroup of non-essentials. These relatively even amounts spent on essentials and non-essentials should be seen in connection with the high-cost borrowers' larger use of *cash withdrawals*, which is likely to be used to purchase a combination of essentials and non-essentials. However, when summing up essentials, non-essentials and cash, high-cost borrowers still only spend approximately 300 DKK more than the comparison group. Hence, the higher expenditure levels of high-cost borrowers are not a signal of them having much larger living expenses in the form of higher spending on essentials, or having more luxurious consumption habits in the form of higher spending on non-essentials. Instead, I find that high-cost borrowers spend more on *transfers*, *financial services* and *gambling*. Transfers can both reflect actual spending (splitting expenses with friends) or genuine transfers of liquidity (.e.g., loans/gifts or loan repayments to friends and family). The higher amounts used on financial services, which mainly consists of debt repayment, indicate that the high-cost borrowers are already at this point debt financing their consumption and that interests and principal repayment constitute a non-negligible share of their expenditures. Finally, and probably most striking, I find that the high-cost borrowers spend much more on gambling than the comparison group. In fact, gambling does by itself account for approximately one third of the difference in total expenditures between high-cost borrowers and the comparison group. Gambling is a prime example of a temptation good (Evans and Popova, 2017), so the high-cost borrowers' high level of spending in this category suggests that they have self-control problems and are prone to temptation spending.

Table 3: Expenditure shares

	Levels (DKK 1000)		Expenditure shares (%)	
	High-cost borrowers	Matched group	High-cost borrowers	Matched group
Essentials	5.6	5.5	32.5	36.4
- Food and daily purchases	2.3	2.3	13.5	15.0
- Housing	1.6	1.6	9.4	10.3
- Mortgage	0.2	0.3	1.2	2.2
- Other essentials	1.4	1.3	8.4	8.9
Non-essentials	3.7	3.9	21.6	25.3
- Retail	1.1	1.1	6.3	7.3
- Going out	0.8	0.9	4.5	5.8
- Vacation	0.3	0.3	1.7	2.1
- Other non-essentials	1.6	1.5	9.1	10.0
Cash	2.8	2.2	16.0	14.3
Transfers	1.9	1.5	10.9	9.8
Gambling	1.0	0.3	5.9	2.1
Financial services	1.0	0.6	6.0	3.7
Other and unknown	1.2	1.3	7.1	8.4

The table decompose total expenditures into expenditure subgroups in levels and as percentage of total expenditures for the high-cost borrowers and for the comparison group matched on age, gender, income and liquidity. Expenditures are measured 12 months before first high-cost loan event. A complete overview of which granular expenditure categories that are included in each subgroup can be found in appendix table D.1.

6 What happens around the first high-cost loan event?

Total expenditures and total income

Figure 1 shows the evolution in total expenditures and total income for the high-cost borrowers, controlling for age and calendar time effects, cf. equation 1. There are three main points to be drawn from this figure. First, high-cost borrowers are consistently spending more than they earn. Repeating the information from table 2, I find that already 12 months before their first high-cost loan event, high-cost borrowers have on average an expenditure to income deficit of approximately 1,600 DKK[22]. This deficit increases as they approach their first high-cost loan event and in month -1, they are approximately spending 3,000 DKK more than they earn.[23] There are several potential explanations for why high-cost borrowers appear to be "living beyond means". One possibility is that they have suffered a persistent shock which has raised their expenditure levels. However, this story is difficult to reconcile with the relatively modest amounts spend on *essentials* documented in table 3. Further, while figure 1 is limited to the time window where the sample is balanced, i.e., month -12 to month 6, I extend the analysis to go from month -30 to month 30 in appendix figure C.2 and find that the high-cost borrowers spend more than they earn even 2.5 years before they start using high-cost credit. This points towards inherent personality traits, e.g., self-control problems, as the most likely explanation to the overspending result.

It is also worth mentioning that the expenditure to income deficit does not appear to be wealth financed. This can be seen by comparing the monthly deficits in figure 1, which are somewhere between 1,500-3,000 DKK each month, with the modest decrease in actual balances documented in appendix table C.2.[24] Instead, high-cost borrowers must credit-finance at least part of their expenditures, for instance by borrowing from midtier-credit companies or from friends and family. This also helps explain why high-cost borrowers already before they borrow from high-cost credit companies have so high spending shares on financial services.[25] Keeping this in mind, one careful interpretation of figure 1 is that high-cost borrowers are steadily exhausting their available resources (including alternative sources of credit) until the point when their best credit option is high-cost credit. This is consistent with previous studies finding that payday loans function as a last credit resort, e.g., (Bhutta et al., 2015).

The second notable insight from figure 1 is the relatively stable evolution in income. There is a small drop around month 0, indicating that some borrowers suffer an income shock. Further, there is also a positive jump around month 2, indicating that some might borrow in expectation of a future income hike. However, the effects are small in magnitude. This suggests that income fluctuations are not an important driver of aggregate loan

[22]I here control for age and calendar time effects and further winsorize at the 99.9% level. Therefore, the figures here do not exactly mirror the figures in table 2.

[23]The expenditure to income deficit depicted in figure 1 is so striking that one might suspect data quality and measurement error to be an issue. One concrete worry is whether I am better able to measure expenditures than income, leading me to overestimate the expenditure to income deficit. To gauge whether this is a problem, I plot figure 1 for the comparison group matched on age, gender, income and liquidity in appendix figure C.3. I here find a stable and reasonable relation between total income and total expenditures, with expenditures that are just around or slightly below income. This reassures me that measurement error is an unlikely driver of the overspending result in figure 1.

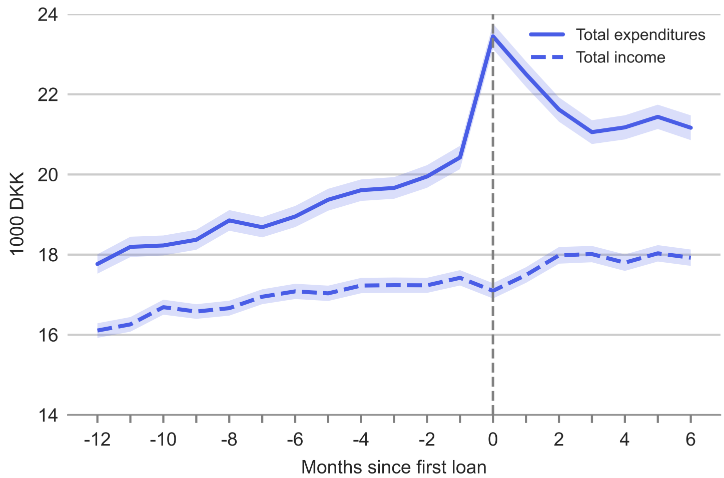
[24]This does on a side note also show that it is neither financed by internal credit, i.e., by borrowing from the bank, as this would also show up on the borrowers' balance sheet information.

[25]I also document a clear association between degree of overspending and use of midtier credit in appendix figure C.4.

demand.[26]

The third and last observation to be made from figure 1 is that the jump in total expenditures around the loan event is both sharp and economically large. This shows that while part of loan proceeds might be used to finance a long-run deficit, a substantial part goes to finance a temporary expenditure increase.

Figure 1: Average total expenditures and total income



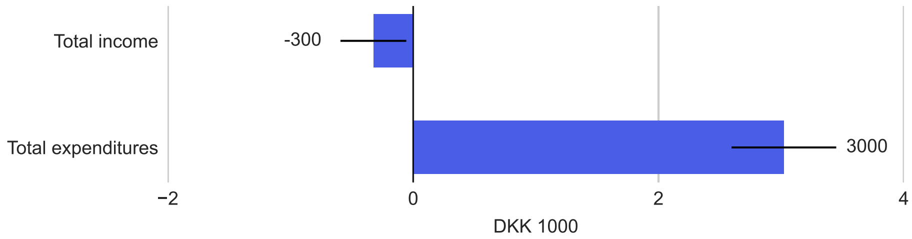
The plot shows predicted values of total expenditures and total income by event time based on equation 1 for the group of high-cost borrowers. All other variables than event times are fixed at sample averages. All outcomes are winsorized at the 99.9 % level. Shaded area indicate 95 % confidence intervals, based on robust standard errors.

I next zoom in on the change in total expenditures and total income from month -1 to month 0 in figure 2. I find that total expenditures jump by nearly 3,000 DKK while income drops by just 300 DKK. Interpreted relative to average loan amount (5,300 DKK) this corresponds to 56% of loan proceeds being used to finance an expenditure increase and 5.6% being used to cover for an income loss. Put differently, the jump in expenditure is larger than the drop in income by an order of magnitude.

Taken together, figure 1 and 2 indicate that borrowers' spending patterns play the lead role in explaining high-cost credit demand and that income fluctuations are only of minor importance. This does not rule out, however, that (some) borrowing can be driven by circumstances. I do find large expenditure jumps around the loan event, which could potentially indicate that borrowers suffer expenditure shocks. I investigate this in the next subsection, where I examine subcategories of total expenditures.

[26] Naturally, these results might be context dependent and one potential explanation for the irrelevance of income fluctuations in explaining high-cost borrowing could be the relatively generous Danish unemployment insurance system. It should, however, be noted, that for people below 30 years, and especially for people below 25 (which a large part of the high-cost borrowers are) the Danish UI system is relatively less generous.

Figure 2: Change from month -1 to month 0 in total expenditures and total income



The plot shows the change from month -1 to month 0 in total expenditures and total income for the group of high-cost borrowers, controlling for age and calendar-time effects, cf. equation 1. All outcomes are winsorized at the 99.9 % level. Horisontal lines indicate 95% confidence intervals, based on robust standard errors.

Subcategories of total expenditure

In figure 3, I show the evolution in six subcategories of total expenditures.[27] The two top panels shows the evolution for *essentials* and *non-essentials*. Both evolve relatively similarly: A positive trend (strongest for *essentials*) in the build-up to the loan event followed by a clear jump in month 0. This indicates that high-cost borrowers increase their consumption over a broad set of goods, including everyday items such as *food & household necessities* as well as non-essentials such as *retail spending*, *going out* and *vacations*. The next two panels show the evolution in *cash withdrawals* and *transfers*. For cash withdrawals, I find a very large spike at month 0. This might reflect that borrowers relying on cash benefit income seek to hide the loan proceeds from authorities to remain eligible for cash benefits.[28] Another possible explanation for the high level of cash withdrawals is that they are used to repay informal loans. For transfers, I find a slight increasing trend in the build-up and again a large jump at month 0. While part of this might reflect social spending, i.e., going out and splitting the costs, I hypothesize that transfers, like cash, are also used to repay informal loans from friends and family. The bottom left panel shows the evolution in *gambling*. For this subcategory, I find a striking pattern with a steep increase in the build-up followed by a large jump in month 0. In crude numbers, the amount spent on gambling more than doubles from month -12 to month 0, despite the fact that high-cost borrowers already in month -12 had spending shares on gambling three times as large as the comparison group matched on age, gender, income and liquidity, cf. table 3.[29] The bottom right panel shows the evolution in *financial services*. I find a positive trend in the build-up, a small increase in month 0 and a relatively large increase from month 1 and onwards, reflecting that borrowers start repaying the high-cost loans almost immediately. The positive trend in the build-up is likely reflecting that high-cost borrowers are credit-financing an (increasing) part of their expenditures, as discussed

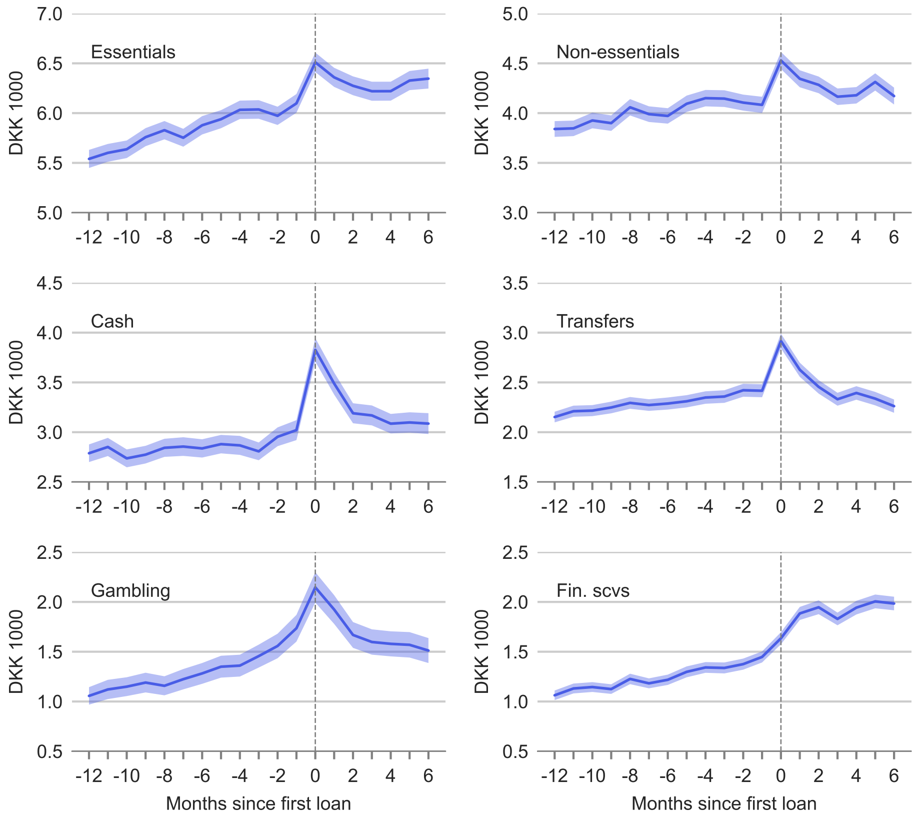
[27] Leaving out the residual category.

[28] To be eligible for cash benefits in Denmark, one cannot hold wealth beyond 10,000 DKK. While cash is in principle included in the relevant wealth measure, it seems plausible that cash is at least perceived to be easier to hide from authorities than bank account deposits.

[29] I explore the high-cost borrowers' gambling behaviour further in appendix F. I document in figure F.1 that gambling is a much more widespread phenomena for the high-cost borrowers than for the comparison group matched on age, gender, income and liquidity. From month -12 to month 6, approximately 60% of the high-cost borrowers gamble at least once, compared to 40% of the age, gender, income and liquidity matched comparison group. Further, the high-cost borrowers are using very large amounts on gambling. The top decile is on average gambling for close to 14,000 DKK each month over these 19 months. That adds up to over a quarter of a million. In figure F.3, I show that gambling is mainly a male phenomena, although the gender gap narrows for older age cohorts and is statistically insignificant for high-cost borrowers aged 50 or older. Lastly, I show in figure F.3 that the increase in average gambling expenditures documented in figure 3 is not just the same individuals increasing their gambling expenditures, but does also reflect that more and more individuals begin gambling.

above.

Figure 3: Evolution in subcategories of total expenditures

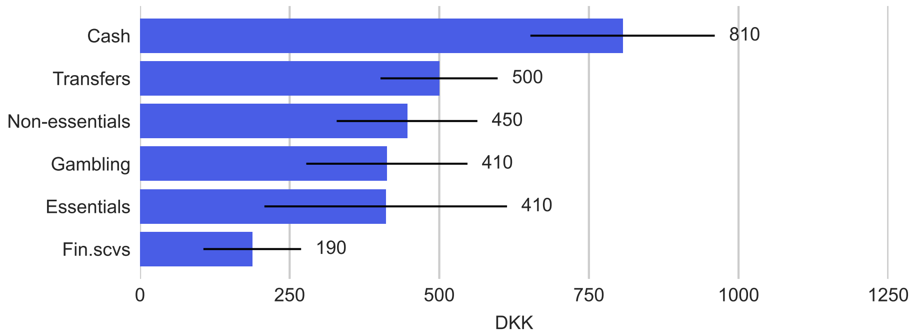


The plot shows predicted values of subcategories of total expenditures by event time based on equation 1 for the group of high-cost borrowers. All other variables than event times are fixed at sample averages. All outcomes are winsorized at the 99.9 % level. Shaded area indicate 95 % confidence intervals, based on robust standard errors.

As for total expenditures and total income, I zoom in on the change from month -1 to month 0 for subcategories of total expenditures in figure 4.[30] Again measured relative to average loan amount, I find that approximately 15% (i.e., 810/5300) of loan proceeds are used on *cash withdrawals*, 9% on *transfers* and around 7-8% each on *non-essentials*, *essentials* and *gambling*. This shows that the popular story of high-cost loans being used solely to finance extravagant consumption such as plasma TVs, restaurant visits, and vacations is not entirely true. Part of loan proceeds are also used to finance everyday expenditures like groceries and other household necessities. But, loan proceeds are still predominantly used to finance non-essential consumption. Ignoring cash and transfers and counting gambling as a non-essential good, I find the month 0 increase in non-essential spending to be more than twice as large as the month 0 increase in essential spending.

[30] The subcategories of total expenditures considered here are relatively aggregated. In appendix figures C.5 and C.6 I repeat figure 4 for more granular expenditure categories.

Figure 4: Change from month -1 to month 0 for subcategories of total expenditures



The plot shows the change from month -1 to month 0 in in subcategories of total expenditures for the group of high-cost borrowers, controlling for age and calendar-time effects, cf. equation 1. All outcomes are winsorized at the 99.9 % level. Horisontal lines indicate 95% confidence intervals, based on robust standard errors.

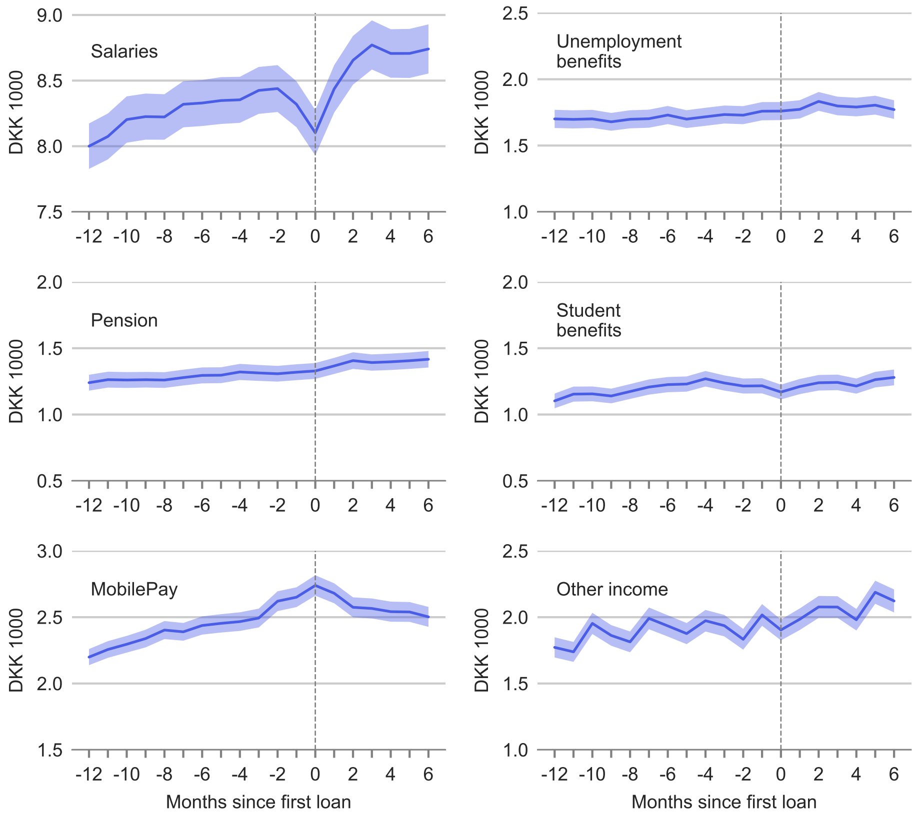
Subcategories of income

Analogously to the breakdown of total expenditures, I also decompose total income into subcategories. Dynamic results of this exercise are presented in figure 5. The top left panel shows the evolution in *salary income*. This is relatively stable up until month -2, but then drops in month -1 and again in month 0, whereafter it quickly recovers and stabilizes on a level somewhat higher than before the loan event. This indicates that at least some individuals experience a temporary shock to their salary income. Note also, that while total income only drops noticeably in month 0, salary income drops already in month -1, indicating that other sources of income keep total income at a relatively high level in month -1. The top right panel shows the evolution in *unemployment benefits* which covers both unemployment insurance and cash benefits. This is basically flat, with virtually nothing happening around the loan event. It is rather surprising that the drop in salary income is not mirrored by an increase in unemployment benefits. This suggests that borrowers do not transition from an employment state into an unemployment state. Instead, borrowers experience a temporary drop in their salary income, for example, because of mistiming in salary payouts. One could also have imagined that the transition from unemployment benefits to cash benefits would be a natural reason to borrow. However, the absence of any drop in unemployment benefits indicate that this is not the case.[31] The two middle panels show two other candidates for predictable income shocks. The left shows the evolution in *pension income*. As with unemployment benefits, one could both imagine this to increase if a lot of borrowers borrow because they experience an income decrease when transitioning from an employment state to retirement. Alternatively, one could also imagine it to decrease if some borrowers borrow because they exhaust their pension savings. However, as for unemployment benefits, the evolution is completely flat, indicating that pension shocks are not a driver of loan demand. The right plot shows the evolution in *student benefits*, which might be more relevant given the age distribution of the borrowers. But as for unemployment benefits and pension income, I find a remarkably flat evolution for *student benefits* too.

[31] One possible explanation could be that that two effects are cancelling each other out: Some borrowers move from salary income to unemployment benefits and thus experience an increase in unemployment benefits while others move from unemployment insurance to cash benefits and thus experiences a decrease in total unemployment benefits. Unfortunately, I cannot separate unemployment insurance from cash benefits to further investigate whether this is the case.

The bottom left plot shows the evolution in *MobilePay income*, which reflects transfers from friends and family. Interestingly, this grows in the build-up and appears to peak just around the loan event. One interpretation of this is that borrowers borrow from friends and family before they turn to high-cost credit. Lastly, the right bottom panel shows the evolution in the residual category *other income*. This is quite volatile and while it drops in month 0, it is difficult to determine whether this is related to the borrowing event or whether it is simply just a question of noise.

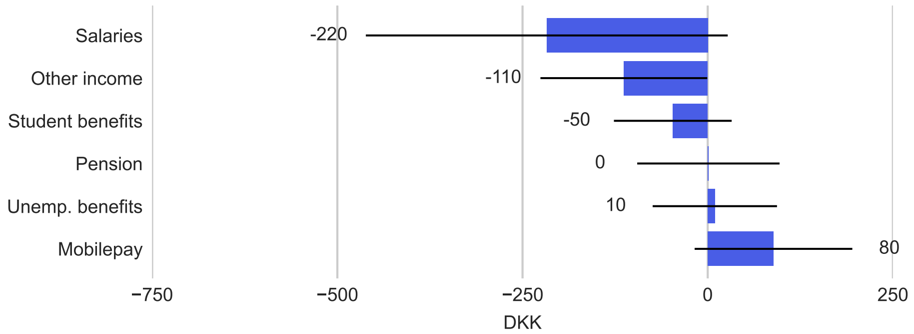
Figure 5: Evolution in subcategories of total income



The plot shows predicted values of subcategories of total income by event time based on equation 1 for the group of high-cost borrowers. All other variables than event times are fixed at sample averages. All outcomes are winsorized at the 99.9 % level. Shaded area indicate 95 % confidence intervals, based on robust standard errors.

Figure 6 shows the change from month -1 to month 0 for subcategories of income. This underlines that salary income drives the observed drop in total income in month 0. There is a small contribution of -50 to the drop from student benefits that was difficult to spot in the dynamic plot. Note also that around one third of the drop in total income in month 0 comes from the residual category "other income". It is debatable whether this should be interpreted as related to the borrowing decision or if it ought to be disregarded as noise, given the very volatile pattern of this income component documented in figure 5. If the latter, then the drop in total income is even smaller than first assumed. However, counteracting this is the fact that salary income drops already from month -2, making the comparison from month -1 to month 0 appear a bit unfair. When compared to month -2, the drop in salary income is around 340 DKK and statistically significant. In the broader picture, however, this is of second order importance. The main takeaway from the decomposition of total income is that the modest drop in total income is not camouflaging any large offsetting movements in subcomponents.

Figure 6: Change from month -1 to month 0 for subcategories of total income



The plot shows the change from month -1 to month 0 in subcategories of total income for the group of high-cost borrowers, controlling for age and calendar-time effects, cf. equation 1. All outcomes are winsorized at the 99.9 % level. Horisontal lines indicate 95% confidence intervals, based on robust standard errors.

Shock indicators

As discussed earlier, a potential reason for why consumers decide to use high-cost credit is that they suffer some kind of adverse event, i.e., a car break down, a job loss, or a sudden health deterioration. In this section, I explore whether such shocks appear to drive credit demand. I present dynamic patterns of shock indicators in figure 7 and changes from month -1 to month 0 in figure 8.

The top left panel of figure 7 shows that the share of borrowers experiencing expenditure shocks is relatively stable over the analysis window. There is a vague indication of an increase around month 0, but as documented in figure 8, the change from month -1 to month 0 is negligible and statistically insignificant. The top right panel of figure 7 shows the evolution for the income shock indicator. I again find a flat evolution in the build-up and a small jump of 0.8 p.p. in month 0. Although this 0.8 p.p. jump is statistically significant on a 5% level, the magnitude is very modest. This suggests that neither expenditure nor income shocks drive aggregate loan demand. In appendix figure C.7 and C.8 I show that these results are robust to varying the shock thresholds. I re-estimate the share of borrowers experiencing expenditure shocks using a 1,000 and a 5,000 DKK threshold (as compared to the 2,500 DKK threshold used here). This changes the levels, but not the qualitative conclusion that borrowers do not appear to suffer expenditure shocks when they borrow. For income shocks, I re-estimate using 25% and 75% thresholds (compared to the 50% threshold used here).[32] For the 75% threshold, I find a significant jump from month -1 to month 0 of 1.7 p.p. Albeit larger than the 0.8 p.p. jump reported in figure C.8, the magnitude is still so small that it cannot be a driver of aggregate loan demand. It does, however, underline that there are *some* borrowers who borrow because they suffer income shocks.

Finally, I also explore whether high-cost borrowers experience health and social shocks in connection with their use of high-cost credit. In figure 8, I show that there is no jump in the share of borrowers experiencing these kind of shocks at the time of borrowing. However, especially for these shocks, one could imagine that the

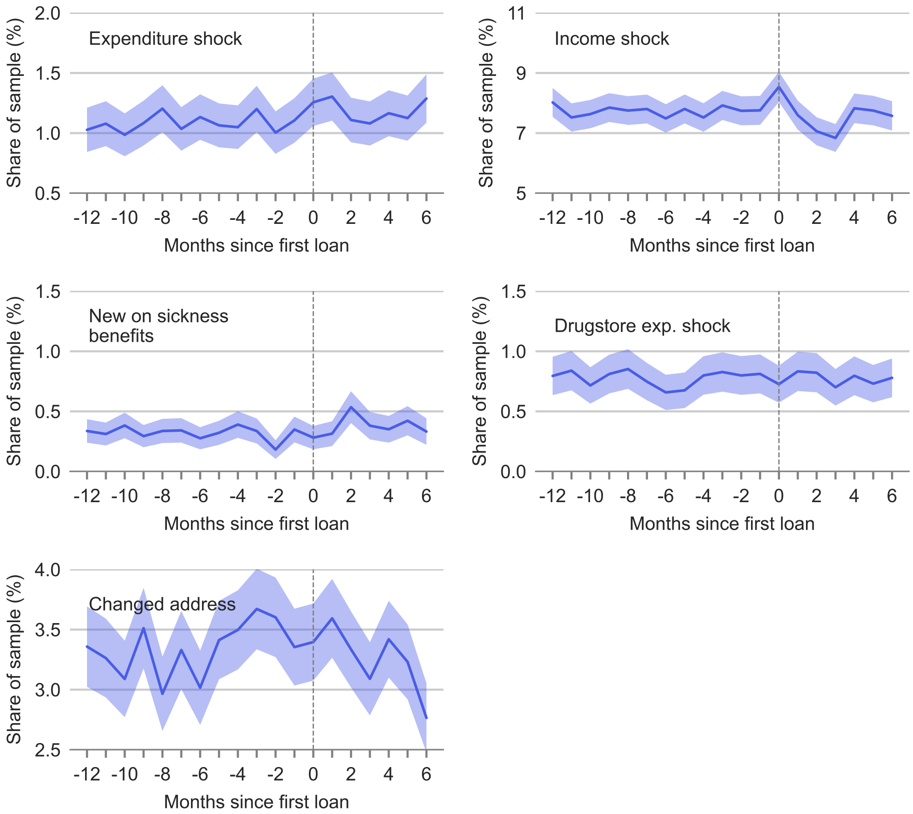
[32] A 25% threshold means that I define an individual to experience an income shock if income in month t is lower than 25% of average income over the three preceding months.

timing is less tight and that shocks might take some time before they materialize into a loan demand. Therefore, borrowers might be suffering health and social shocks in the build-up to the loan event. But if this was the case, then one would also expect the share of borrowers experiencing shocks to be increasing in the build-up to the loan event. The flat pre-trends documented in the middle and bottom panels of figure 7 suggest that this is not the case. I therefore conclude that health and social shocks are also unlikely to be driving loan demand.

One might ask whether the absence of shock-driven borrowing is rather a sign that the shock indicators are ill-defined, i.e., that they do not capture adverse events where consumers' demand for liquidity is likely to jump. To assess whether this is the case, I investigate to what extent there is a correlation between the shock indicators and two alternative measures of liquidity demand, namely receiving parental financial support and borrowing from midtier credit companies. The results of this exercise is presented in appendix table C.3. I find clear indications that especially the expenditure and income shocks are associated with an increased liquidity demand. For the health and social shock measures, I find only borderline significant correlations, but the coefficients generally point in the expected direction. Keeping in mind that both of the alternative measures of liquidity demand are only crude proxies, I take this as evidence that the shock measures do in fact capture events where liquidity demand is higher.[33]

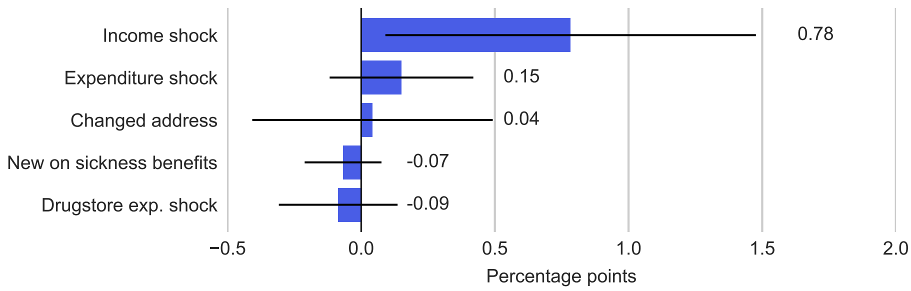
[33] As mentioned in section 4, I adopt the expenditure and income shock indicators from Andersen et al. (2020). They explore whether these shocks are associated with an increase of parental financial support, but are much better able to measure parental financial support as they have successfully merged the transaction data with administrative data enabling them to directly link individuals to their parents. They find that both shocks are strongly correlated with parental financial support, which too lends credibility to the usefulness of the shock indicators.

Figure 7: Evolution in shock indicators



The plot shows predicted values for the binary shock indicators by event time based on equation 1 for the group of high-cost borrowers. All other variables than event time are fixed at sample averages. Shaded area indicate 95 % confidence intervals, based on robust standard errors.

Figure 8: Change from month -1 to month 0 in shock indicators



The plot shows the change from month -1 to month 0 in the binary shock indicators for the group of high-cost borrowers, controlling for age and calendar-time effects, cf. equation 1. Horisontal lines indicate 95% confidence intervals, based on robust standard errors.

7 Conclusion

The aim of this paper is to investigate why consumers use high-cost credit. I hypothesize two competing drivers of loan demand, inspired by the public debate surrounding high-cost credit. One hypothesis is that consumers use high-cost credit in situations where they suffer from adverse events, for instance in the form of income or expenditure shocks. Alternatively, borrowing is not shock-triggered, but is instead driven by borrowers' inherent personality traits, which lead them to consume more in the short run than they would prefer to in the long run.

To assess the hypothesis that borrowing is triggered by adverse events, I define a range of binary shock indicators and investigate whether there is an increase in the share of borrowers experiencing shocks around the time of borrowing. The evidence does generally not support this hypothesis, as there are no indications of high-cost borrowers experiencing expenditure, health, or social shocks. There is likely a small group of borrowers who suffer income shocks in connection with their first high-cost loan, but the magnitude is too small for income shocks to be an important factor in explaining aggregate loan demand.

It is more challenging to test the alternative hypothesis that borrowing is driven by borrowers' inherent personality traits, as there is per definition no time variation in these. However, throughout the analysis, I find evidence pointing towards that the high-cost borrowers are more present-biased and more prone to temptation spending than other consumers. I document that high-cost borrowers persistently spend more than they earn, that they tend to spend large amounts on gambling, and that they have paycheck sensitivities that are double that of normal consumers, pointing towards high degrees of present-bias. Given that I further find large expenditure increases at the time of borrowing, this suggests a dominant role for personality traits, specifically a lack of self-control, in explaining loan demand.

If borrowing is predominantly explained by high-cost borrowers having personality traits that lead them to consume more in the short run than they would like to in the long run, then it is likely that access to high-cost credit is harmful for consumers (Laibson, 1997). However, high-cost borrowers are on an unsustainable consumption trajectory long before they start using high-cost credit. And while gambling jumps around the time of borrowing, the stark increases in gambling expenditures in the build-up to the first loan event indicate that it is gambling that leads to high-cost borrowing and not vice versa. Further, there are also *some* who borrow because of adverse circumstances, i.e., because they suffer a temporary income loss. For these borrowers, loan access is likely to be welfare improving as it allows them to smoothen their consumption. Taken together, this suggests that restricting loan access is at most a second-best policy and that a more holistic approach is warranted. Optimal policy should aim at reducing behavioural biases among consumers, e.g., by improving financial literacy or by providing tools that help consumers monitor their expenditures and cope with self-control problems.

References

Agarwal, Sumit, Paige Marta Skiba, and Jeremy Bruce Tobacman (2009). "Payday Loans and Credit Cards: New Liquidity and Credit Scoring Puzzles?" *American Economic ReviewAmerican Economic Review* 99.2, pp. 412–417.

Andersen, Asger Lau, Niels Johannesen, and Adam Sheridan (2020). Bailing out the Kids: New Evidence on Informal Insurance from one Billion Bank Transfers. Working paper.

Baugh, Brian (2016). Payday borrowing and household outcomes: Evidence from a natural experiment. Working paper.

Bhutta, Neil, Jacob Goldin, and Tatiana Homonoff (2016). "Consumer Borrowing after Payday Loan Bans". *The Journal of Law and Economics* 59.1, pp. 225–259.

Bhutta, Neil, Paige Marta Skiba, and Jeremy Tobacman (2015). "Payday Loan Choices and Consequences". *Journal of Money, Credit and Banking* 47.2-3, pp. 223–260.

Carrell, Scott and Jonathan Zinman (2014). "In Harm's Way? Payday Loan Access and Military Personnel Performance". *Review of Financial Studies* 27.9, pp. 2805–2840.

Carvalho, Leandro, Arna Olafsson, and Dan Silverman (2019). Misfortune and Mistake: The Financial Conditions and Decision-making Ability of High-cost Loan Borrowers. Working paper.

DCCA (2015). Markedet for Kviklån. Technical report. Danish Competition and Consumer Authority.

Dobridge, Christine L. (2016). "For Better and for Worse? Effects of Access to High-Cost Consumer Credit". *Finance and Economics Discussion Series 2016-056. Board of Governors of the Federal Reserve System (U.S.)*

DR (2019). Vild vækst i kviklån. URL: https://www.dr.dk/nyheder/penge/vild-vaekst-i-kviklaan-danskerne-vaelter-sig-i-smaa-laan-med-hoeje-omkostninger, visited on 30-05-2022.

Evans, David K. and Anna Popova (2017). "Cash transfers and temptation goods". *Economic Development and Cultural Change* 65.2, pp. 189–221.

Gathergood, John (2012). "Self-control, financial literacy and consumer over-indebtedness". *Journal of Economic Psychology* 33.3, pp. 590–602.

Gathergood, John, Benedict Guttman-Kenney, and Stefan Hunt (2018). "How Do Payday Loans Affect Borrowers? Evidence from the U.K. Market". *The Review of Financial Studies* 32.2, pp. 496–523.

Gul, Faruk and Wolfgang Pesendorfer (2001). "Temptation and Self-Control". *Econometrica* 69.6, pp. 1403–1435.

Harris, Christopher and David Laibson (2013). "Instantaneous Gratification". *The Quarterly Journal of Economics* 128.1, pp. 205–248.

Jørring, Adam T (2020). Financial Sophistication and Consumer Spending. Working paper.

Kreiner, Claus Thustrup, Søren Leth-Petersen, and Louise Charlotte Willerslev-Olsen (2020). "Financial Trouble Across Generations: Evidence from the Universe of Personal Loans in Denmark". *Economic Journal* 130.625, pp. 233–262.

Kuchler, Theresa and Michaela Pagel (2021). “Sticking to your plan: The role of present bias for credit card paydown”. *Journal of Financial Economics* 139.2, pp. 359–388.

Laibson, David (1997). “Golden eggs and hyperbolic discounting”. *Quarterly Journal of Economics* 112.2, pp. 443–478.

Laibson, David et al. (2018). Estimating Discount Functions with Consumption Choices over the Lifecycle. Working paper.

Meier, Stephan and Charles Sprenger (2010). “Present-Biased Preferences and Credit Card Borrowing”. *American Economic Journal: Applied Economics* 2.1, pp. 193–210.

Melzer, Brian T. (2011). “The Real Costs of Credit Access: Evidence from the Payday Lending Market*”. *The Quarterly Journal of Economics* 126.1, pp. 517–555.

— (2018). “Spillovers from Costly Credit”. *The Review of Financial Studies* 31.9, pp. 3568–3594.

Morse, Adair (2011). “Payday lenders: Heroes or villains?” *Journal of Financial Economics* 102.1, pp. 28–44.

Skiba, Paige Marta and Jeremy Tobacman (2019). “Do payday loans cause bankruptcy?” *Journal of Law and Economics* 62.3.

Skiba, Paige Marta and Jeremy Bruce Tobacman (2008). Payday Loans, Uncertainty and Discounting: Explaining Patterns of Borrowing, Repayment, and Default. Working paper.

Zaki, Mary (2016). Access to Short-Term Credit and Consumption Smoothing within the Paycycle. Working paper.

Zinman, Jonathan (2008). “Restricting Consumer Credit Access: Household Survey Evidence on Effects around the Oregon Rate Cap”. *Journal of Banking and Finance* 34, pp. 546–556.

Appendices

A Identification of high-cost credit suppliers

A.1 List of comparison websites

- https://kviklaan-guide.dk/
- https://www.pengeinfo.dk/kviklan/
- https://moneylender.dk/kviklån
- https://www.mikonomi.dk/penge/kviklaan
- https://lavprislån.dk/
- https://kviklanet.dk/
- https://p5.dk/index.php
- https://moneybanker.dk/kviklaan/
- https://tjek-laan.dk/kviklaan
- https://valutaomregneren.dk/sammenlign/kviklaan
- https://credi.dk/kviklaan-sammenlign/
- https://financer.com/dk/laan-penge/kviklaan/
- https://fair-laan.dk/

A.2 List of high-cost credit companies

Company	**Identification method**
Ferratum	2015 report
Kvikautomaten	2015 report
Vivus	2015 report
Trustbuddy	2015 report
Mikrokredit	2015 report
Mobillån	2015 report
Folkia	2015 report
Zaplo	Comparison website
Bedre Kredit	Comparison website
Cashper	Comparison website
Kreditnu	Comparison website
Kronelån	Comparison website
Simbo	Comparison website
Kvikto	Comparison website
Kassekreditten	Comparison website
Folkelånet	Comparison website
Minifinans	Comparison website
Turbolån	Comparison website
Bonuslån	Comparison website
Lendon	Comparison website
Gokredit	Comparison website
Nordcredit	Comparison website
Momentlån	Comparison website
Mozipo	Found in data
247lån	Found in data

B Documentation of comparison websites and loan products

Figure B.1: Folkia product information February 2016

Retrieved from web.archive.org in July 2021.

Figure B.2: Vivus loan terms page 1 August 2016

Lånevilkår
VIVUS.DK (4finance ApS), CVR-nr. 32 55 78 64

1. Information om selskabet og lån
VIVUS.DK (som er ejet af 4finance ApS) kan bevilge lån til en fysisk person (herefter "kunden"), som er mindst 20 år, er dansk statsborger med dansk CPR-nummer og folkeregisteradresse, har et gyldigt Nem ID og som af VIVUS.DK vurderes kreditværdig.

Kreditværdighed hos VIVUS.DK betyder at kunden ikke står registreret i et af følgende skyldnerregistre:

1. RKI (Experian)
2. Debitor Registret

For at kunne få bevilliget lån, er der ydermere krav om, at kunden oplyser:

- En aktiv e-mailadresse, som benyttes af kunden,
- Et dansk telefonnummer, som benyttes af kunden, samt
- En dansk bankkonto, som tilhører kunden

2. Lånebeløb og omkostninger
Kunden kan bevilges lån på mellem 100,00 og 10.000,00 kr. Løbetiden for lånet er 1-30 dage. De gældende priser kan ses på VIVUS.DK startside.

Første gang der optages et lån hos VIVUS.DK, kan kunden låne op til 4.000,00 kr. Når dette lån er tilbagebetalt rettidigt, stiger kundens maksimale lånebeløb hos VIVUS.DK med 1.000,00 kr. Det maksimale lånebeløb hos VIVUS.DK er 10.000,00 kr.

Hvis kunden ikke har udnyttet sit lånemaksimum, kan kunden under låneforholdet anmode om at forhøje lånebeløbet op til det til enhver tid gældende lånemaksimum. Kunden kan anmode om at forlænge låneperioden med 7 dage, 14 dage eller 30 dage, forlængelsen af låneperioden sker ved indbetaling af det til enhver tid gældende fastsatte forlængelsesgebyr.

Kunden kan ikke bevilges et nyt lån, før et allerede bevilget lån er tilbagebetalt.

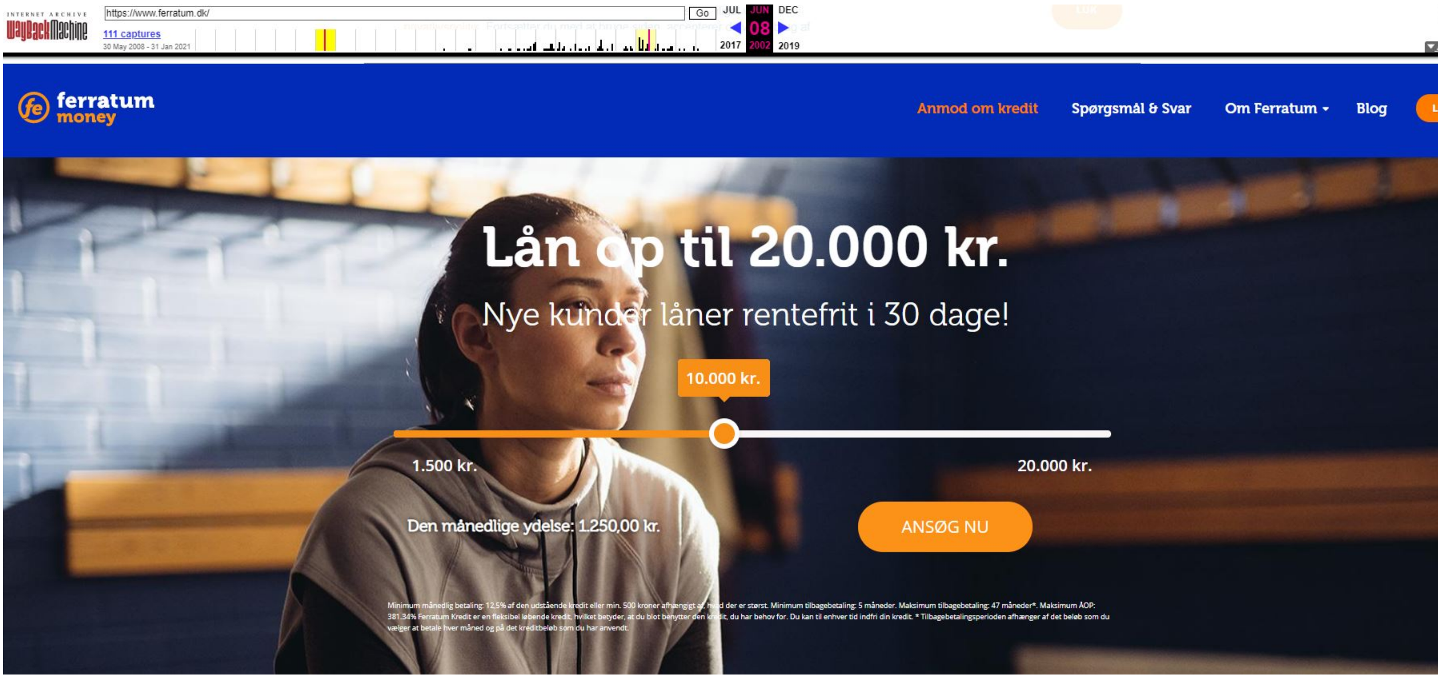
Eksempel på ovenstående:

*Kunde A låner 3.000,00 kr. ved VIVUS.DK i 30 dage. Renteudgiften på dette lån udgør f.eks. 570,00 kr. (= 3.000,00 kr. * 19,00 %). Kunde A vælger efter 30 dage at forlænge lånet yderligere 30 dage. For at oprettelsen af forlængelsen kan gennemføres, indbetaler kunden 570,00 kr. til VIVUS.DK (= (19,00 % / 30 dage * 30 dages forlængelse) * 3.000,00 kr.). Ved lånets forfaldsdato (efter i alt 60 dage) indbetales 3.570,00 kr. (lånebeløb plus oprindelige renter) til VIVUS.DK.*

Yderligere omkostninger

Retrieved from web.archive.org in July 2021.

Figure B.3: Ferratum loan August 2018

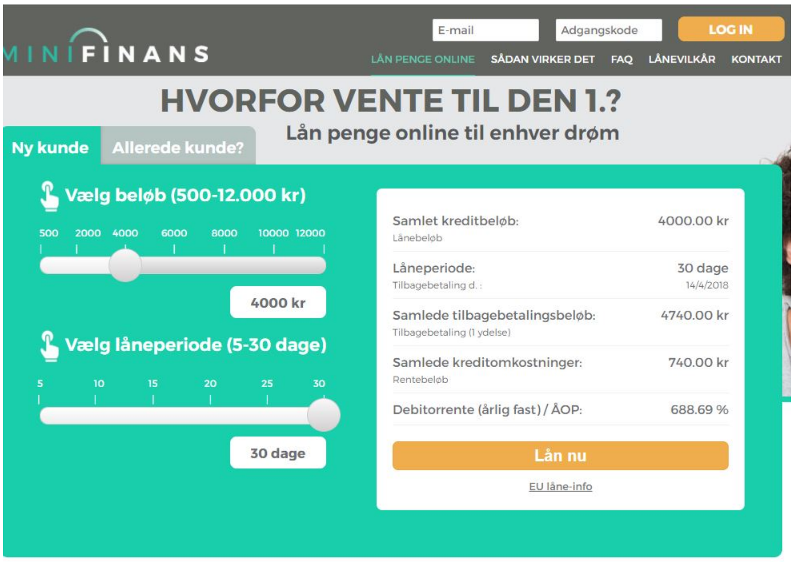


Retrieved from web.archive.org in July 2021.

Figure B.4: Turbolån loan April 2018

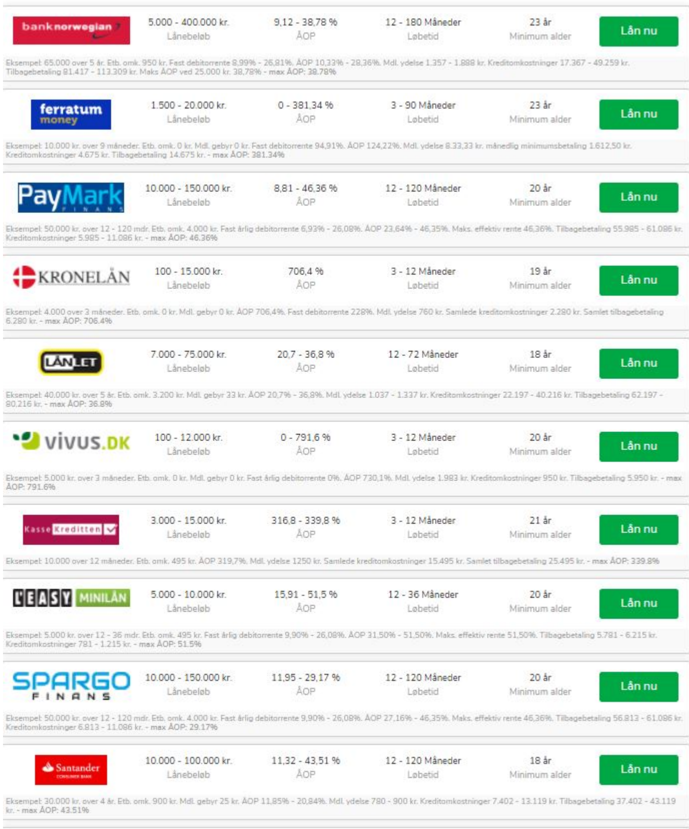
Retrieved from web.archive.org in July 2021.

Figure B.5: Minifinans loan March 2018



Retrieved from web.archive.org in July 2021.

Figure B.6: Comparison website, August 2018



Retrieved from web.archive.org in May 2022.

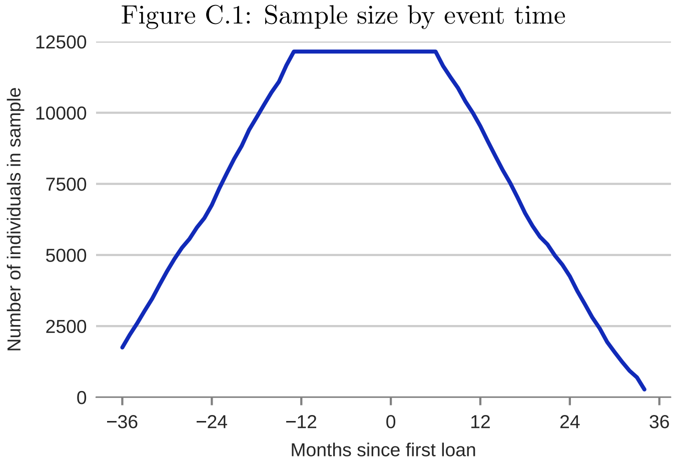
C Appendix figures and tables

Table C.1: Comparison of the bank customer sample and the entire Danish population

	Random sample of bank customers	Population
Demographics		
Avg. Age (years)	48.1	49.1
18-30 years old (%)	20.7	19.9
30-50 yers old (%)	32.1	31.3
50+ years old (%)	47.2	48.8
Share female (%)	51.9	50.6
Socio-economic indicators		
Receives labor income (%)	62.2	60.5
Receives unemployment benefits (%)	9.4	8.7
Receives pension income (%)	28.4	28.3
Receives student benefits (%)	8.9	7.1
Receives sickness benefits (%)	0.8	1.2
Household finances		
Total monthly income (1000 DKK)	22.2	20.9
Account balances (1000 DKK)	140.7	158.1

This table assesses the representativeness of the bank customer sample by comparing summary stats for the randomly sampled comparison group of bank customers (column 1) with the entire adult population of Denmark (column 2). The values in column (1) replicates column (4) in table 2, albeit only for those variables where it is possible to find equivalent publicly available statistics from Statistics Denmark. All figures in column (2) are measured in 2018, using the most comparable variable definitions and sample restrictions. There are some key differences between the two samples: *Receiving labor income* and *total monthly income* in the population sample are averages for individuals above 20 years (compared to 18 years for the bank customer sample). All other socio-economic indicators in the population sample are averages for individuals above 16 years (again, compared to 18 years for the bank customer sample). Lastly, *account balances* in the population sample is based on all deposits on bank accounts (compared to only liquid accounts, cf. section 3, for the bank customer sample).

Figure C.1: Sample size by event time



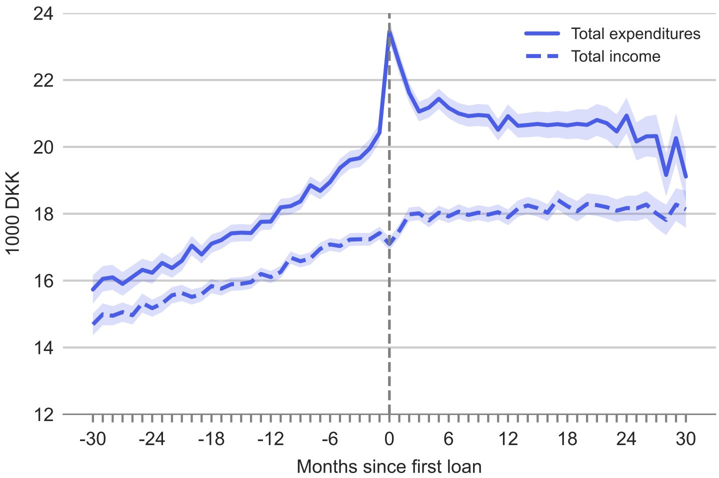
The plot shows the number of individuals in the sample at each event time. Note that the sample is constructed to be balanced from month -12 to 6, which explains the flat plateau in the middle of the plot.

Table C.2: Account balances and available liquidity 12 months and 1 month before first loan

	Percentiles								
	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90
Account balances									
Month -12	-13677.5	-1803.9	416.9	959.0	1603.8	2415.3	3713.4	6557.3	15695.2
Month -1	-16078.7	-3802.3	111.6	780.5	1367.3	2096.9	3091.2	4748.8	9094.3
Available liquidity									
Month -12	224.1	673.6	1198.6	1841.0	2711.3	4194.1	6970.4	13335.1	32643.5
Month -1	148.0	626.4	1113.9	1736.8	2432.2	3495.2	5233.1	9011.7	23938.9

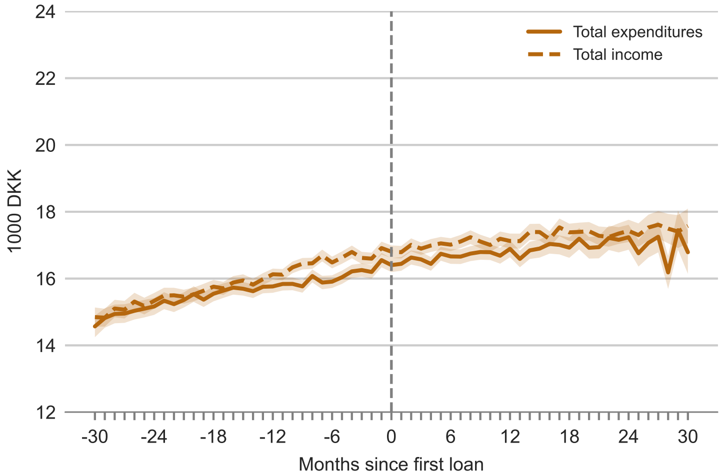
The table shows the distribution of account balances and available liquidity for the group of high-cost borrowers 12 months and one month before first high-cost loan event.

Figure C.2: Average total expenditures and total income for high-cost borrowers, month -30 to month 30



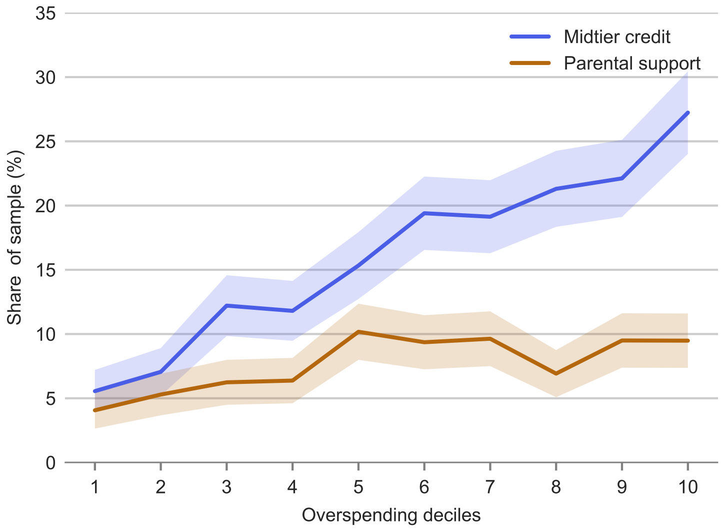
The plot shows predicted values for total expenditures and total income by event time based on equation 1 for the group of high-cost borrowers. All other variables are fixed at sample averages. All outcomes are winsorized at the 99.9 % level. Shaded area indicate 95 % confidence intervals, based on robust standard errors. Note that the sample is unbalanced before month -12 and after month 6.

Figure C.3: Average total expenditures and total income for comparison group matched on age, gender, income and liquidity



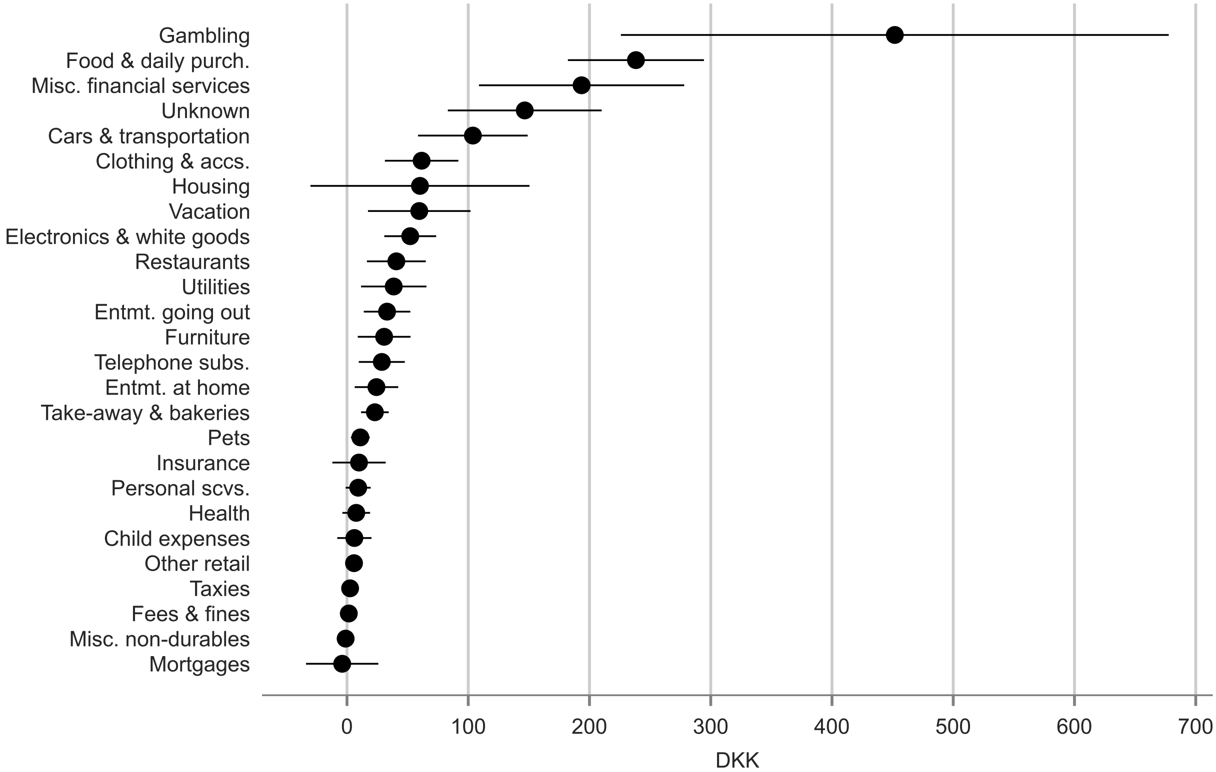
The plot shows predicted values for total expenditures and total income by event time based on equation 1 for the comparison group matched on age, gender, income and liquidity. All other variables are fixed at sample averages. All outcomes are winsorized at the 99.9 % level. Shaded area indicate 95 % confidence intervals, based on robust standard errors clustered at the individual level. Note that the sample is unbalanced before month -12 and after month 6.

Figure C.4: Use of midtier credit and parental financial support by deciles of overspending



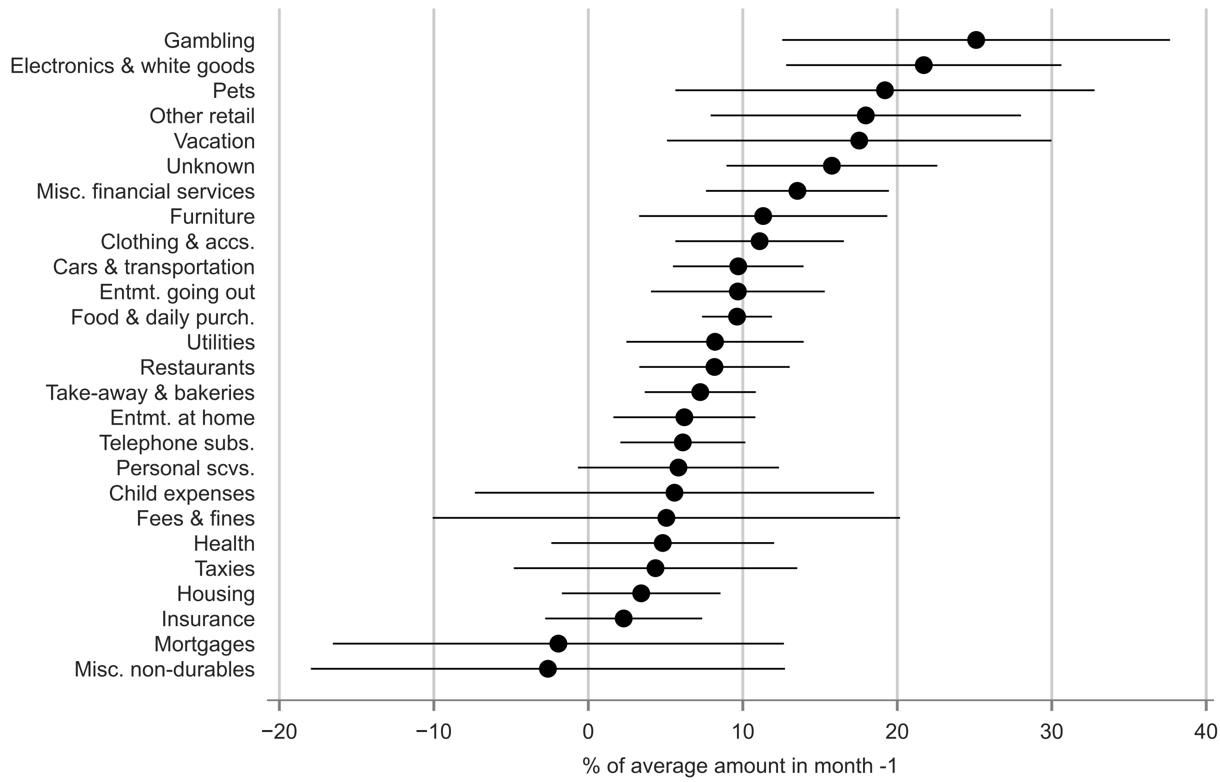
The plot shows by decile of overspending the share of the sample that over the period from month -12 to month -1 borrows for more than 500 DKK from a midtier credit company (blue curve) or receives at least 500 in financial support from their parents (orange curve). The sample is restricted to those who are overspending in this period, i.e. those whose total expenditures exceed total income across month -12 to month 1. Shaded area indicate 95 % confidence intervals, based on robust standard errors.

Figure C.5: Spending response at first loan event for granular categories of total expenditures, in levels



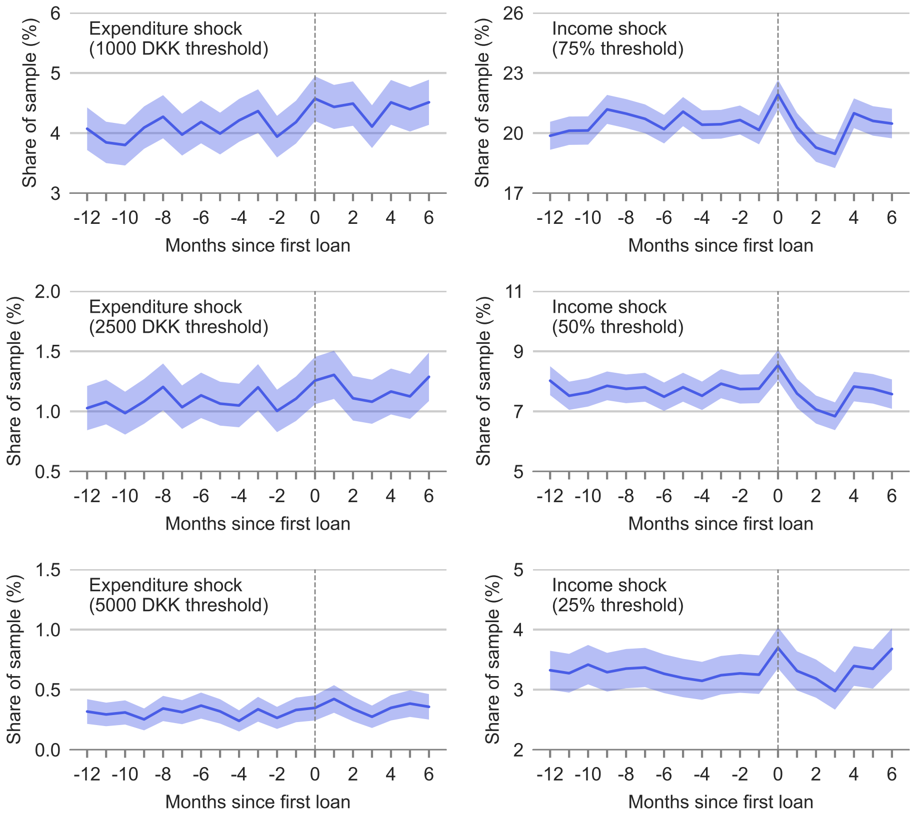
The plot shows the change from month -1 to month 0 in granular expenditure categories for the group of high-cost borrowers, controlling for age and calendar-time effects, cf. equation 1. All outcomes are winsorized at the 99.9 % level. Horisontal lines indicate 95% confidence intervals, based on robust standard errors.

Figure C.6: Spending response at first loan event for sub categories of spending, relative to month -1 values



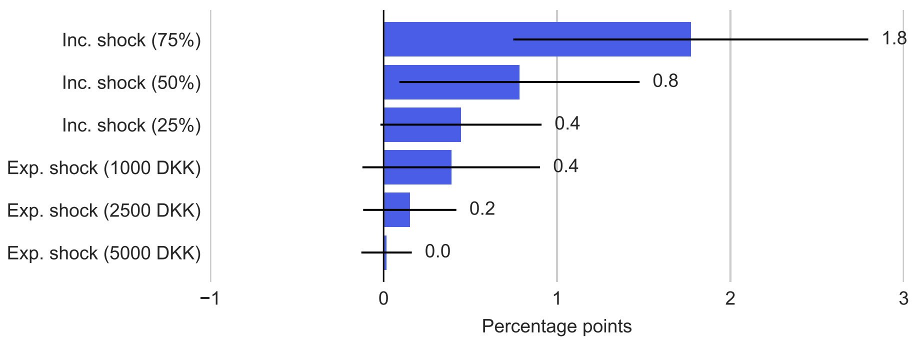
The plot shows the change from month -1 to month 0 in granular expenditure categories for the group of high-cost borrowers, controlling for age and calendar-time effects, cf. equation 1. All outcomes are winsorized at the 99.9 % level and measured relative to the average amount spend on each granular category in month -1. Horisontal lines indicate 95% confidence intervals, based on robust standard errors.

Figure C.7: Expenditure and income shock indicators with alternative thresholds



The plot shows predicted values for the binary expenditure- and income shock indicators by event time based on equation 1 for the group of high-cost borrowers. All other variables than event times are fixed at sample averages. All outcomes are winsorized at the 99.9 % level. Shaded area indicate 95 % confidence intervals, based on robust standard errors.

Figure C.8: Change from month -1 to month 0 in expenditure shock and income shock indicators with alternative thresholds



The plot shows the change from month -1 to month 0 in alternative measures of expenditure and income shocks expenditure for the group of high-cost borrowers, controlling for age and calendar-time effects, cf. equation 1. Horisontal lines indicate 95% confidence intervals, based on robust standard errors.

Table C.3: Shock indicators and alternative measures of liquidity demand

	Shock indicator				
	Expenditure shock	Income shock	New on sickness benefits	Drug-store exp. shock	Changed address
Panel A					
Intercept	0.64***	6.19***	0.79***	0.13***	3.34***
	(0.05)	(0.14)	(0.05)	(0.03)	(0.09)
Midtier credit	1.97***	1.0*	0.32	0.14	0.19
	(0.32)	(0.45)	(0.21)	(0.13)	(0.29)
Panel B					
Intercept	0.64***	6.18***	0.79***	0.14***	3.33***
	(0.05)	(0.14)	(0.05)	(0.03)	(0.09)
Parent financial support	0.45**	2.74***	0.16	-0.04	0.74**
	(0.15)	(0.4)	(0.13)	(0.07)	(0.25)

This table shows estimates of regressing the five shock indicators on binary indicators of borrowing 500 or more DKK from a midtier credit company (panel A) or receiving 500 or more DKK from parents in financial support (panel B). All regressions include individual, month and year fixed effects. Robust standard errors reported in parentheses. ***, ** and * indicate significance on a 0.001, 0.01 and 0.05 level, based on robust standard errors. Estimation is based on all observations for both the high-cost borrowers and the comparison group matched on age, gender, income and liquidity, using data going up to one month before first high-cost loan event.

D Grouping of spending categories

I follow the methodology developed in Jørring (2020) to group expenditure categories into essentials and non-essentials. For this exercise, I draw a distinct large sample of bank customers, consisting of approximately 250,000 individuals, whom I can follow for several years. I restrict to individuals who have an ”expenditure to income” ratio (i.e. an *average propensity to consume*) of maximum 2, to ensure that I only include individuals whose income is well captured. I also restrict to individuals aged 25 or older to avoid spurious effects from children still living with their parents. I collapse data to the yearly frequency and for each expenditure category, estimate the following regression:

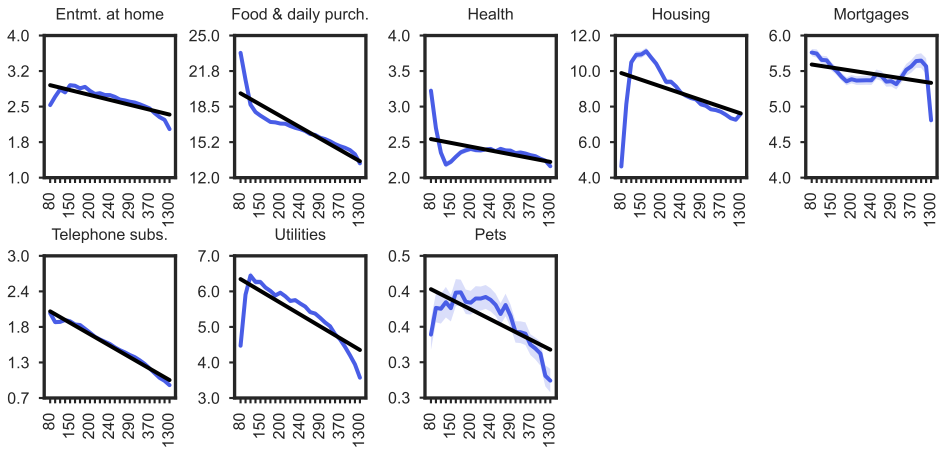
$$spend\_share_{yit} = \sum_{b=1}^{25} \beta_b income_{bit} + \alpha_1 age_{it} + \alpha_2 gender_i + \alpha_3 year_t + \alpha_4 homeowner_{it} + \epsilon_{it} \tag{2}$$

Where $spend\_share_{yit}$ is individual *i's* spending on expenditure category y in year t relative to same individual's total expenditures in the same year. $income_{it}$ is a vector of 25 evenly sized income bins, age_{it} is a vector of 10 age bins, $gender_i$ is a dummy for whether individual i is female or male, $year_t$ is a year fixed effect and finally $homeowner_{it}$ is a dummy capturing whether individual i appears to be a homeowner in year t (proxied for by positive mortgage payments). Figure D.1 shows for each expenditure category the predicted values for each income bin with all other variables fixed at sample averages. To make it easier to detect the overall trend of the engel-curves, I also plot a trend curve based on an alternative version of the regression above where income enters linearly.

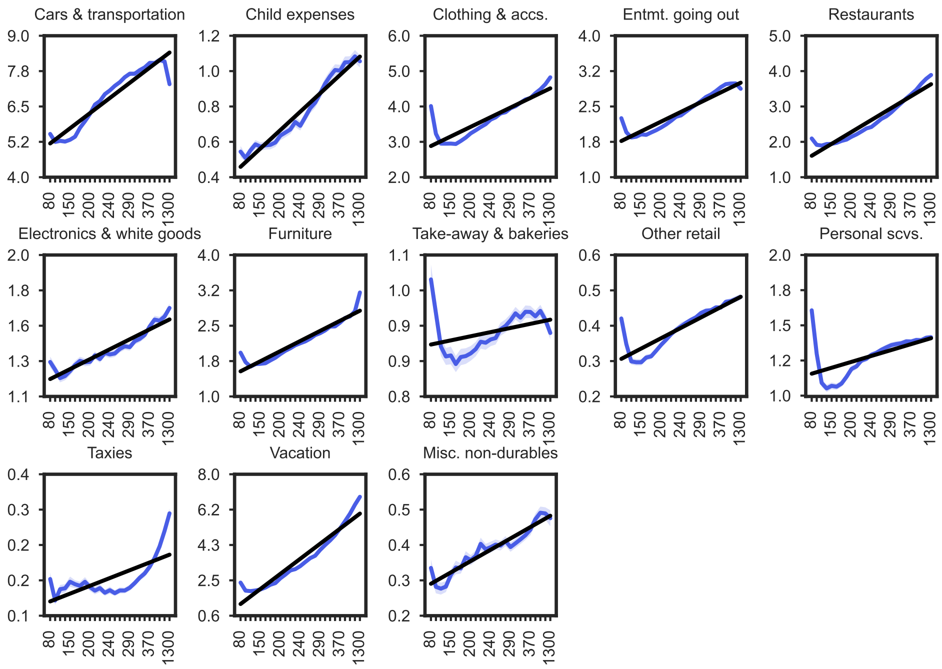
Following Jørring (2020), I define expenditure categories as *essentials* if their budget shares decrease with income. Similarly, I define expenditures as *non-essentials* if their budgets shares increase with income. The top panel of figure D.1 plots the five expenditure categories which are identified as essentials, and the mid-panel plots the 13 categories identified as non-essentials. Finally, the bottom panel plots the remaining two categories, where the engel curve exercise doesn't result in any obvious grouping. These are *Fees & fines* and *Insurance*. I summarize the groupings in table D.1.

Figure D.1: Grouping of expenditure subcategories

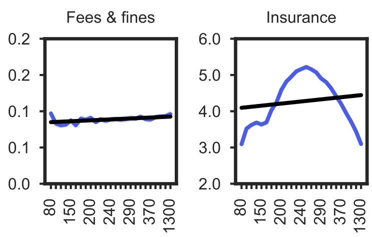
(a) Essentials



(b) Non-essentials



(c) Other



The plot shows engel-curves for subcategories of total expenditures, following equation 2. Y-axes show predicted shares of total expenditures, with all other variables than income bins evaluated at the sample averages. X-axes show mean income in each of the 25 income bins. Shaded areas show 95% confidence intervals, based on robust standard errors. Linear curves are based on an alternative specification of equation 2, where income bins enter linearly.

Table D.1: Grouping of expenditure categories

Expenditure group	**Expenditure categories in group**
Essentials	Food & daily purchases; Entertainment at home; Health-related expenditures; Housing; Mortgage; Pets; Telephone subscriptions; Utilities
Non-essentials	Cars & transportation; Child expenses; Clothing & accessories; Going out (entertainment); Going out (restaurants); Electronics and white goods; Furniture; Luxury food (take away and bakeries); Other retail, Personal services and wellness; Taxies; Vacation
Gambling	Gambling
Financial services	Financial services
Cash	Cash withdrawals
Transfers	Transfers
Other and unknown	Fees & fines; Insurance; Unlabelled expenditures

E Measure of present-bias

I construct a measure of present-bias by following Kuchler and Pagel (2021), who show how present-biased consumers will have a higher consumption sensitivity to income fluctuations and how this empirically can be used to assess individual present-bias using high-frequency data on expenditures and income. As in Kuchler and Pagel (2021), I define a sample of individuals for whom I observe regular "paychecks". Given my Danish context, I allow the paycheck frequency to differ from 14 days to 31 days, keeping in mind that most types of income are paid out at a monthly frequency in Denmark.[34] Further, as my sample is only loosely attached to the labour market, I use a broad definition of "paycheck", including all types of salaries and government transfers. To ensure that I am only picking up actual paycheck events, I first calculate individuals' median paycheck over the full time period.[35] I then drop paycheck events that are lower than 90% of the median paycheck and restrict to individuals where I observe at least 12 paycheck events.

While the theoretical model developed in Kuchler and Pagel (2021) concerns total consumption, they limit themselves in their empirical application to a subset af expenditure categories for which the window between purchase and consumption is plausible as short as possible. I follow this to the extent possible to make a broad definition of short-run consumables as the sum of the following expenditure categories: *Food & daily purchases*, *entertainment away from home*, *restaurants & bars* and *gambling*.[36] Again, following Kuchler and Pagel (2021), I also define a narrow subset of expenditure categories for which the link between purchase and consumption is plausibly even tighter: *Entertainment away from home* and *restaurants & bars*. I coin this narrow subset as "Going out".

I then collapse data on a weekly level (letting each week start on the day that an individual receives her paycheck) and estimate the following equation for each group, i.e., for the high-cost borrowers and for each of the three comparison groups, separately:

$$E_{it} = \alpha_i + \gamma_1 payweek_{it} + \Psi X_{it} + \epsilon_{it} \tag{3}$$

Where E_{it} is individual average short-run consumables expenditures, $payweek_{it}$ is a dummy equal to one if individual i receives income in that week, α_i is individual fixed effects and X_{it} is a vector containing controls for day of week[37] and month in year. The parameter of interest is γ_1, which captures pay-check sensitivity.

Kuchler and Pagel (2021) apply a log-transformation to the dependent variable. This is not appropriate in my setting where many individuals have weeks with no purchases of short-run consumables, resulting in a

[34] Kuchler and Pagel (2021) are more strict in this regard and only consider a subsample of individuals who receive their paycheck at a biweekly level. They do, however argue, that the exact frequency is not crucial, as long as it is reasonably high-frequency, which a monthly frequency likely is.

[35] The full time period being at least 12 months before first high-cost loan event and six months after, but usually longer.

[36] Relative to Kuchler and Pagel (2021) I don't include *fuel* as I cannot separate it out from other transport-related expenditures. I also don't include *entertainment at home* (which could be video games, media subscriptions and the like) since there is a potential for a large time gap between purchase and consumption for this category. Lastly, I include gambling expenditures, although this isn't included in Kuchler and Pagel (2021) as this is also a type of consumption where the link between purchase and consumption is presumably tight.

[37] As I am using 7-day aggregated data, I use the first day of this 7-day window.

large number of zero observations. Instead, I scale the dependent variable with the individual level average weekly expenditures on short-run consumables across the full sample period. This gives the dependent variable an interpretation as weekly expenditures on short-run consumables relative to normal weekly expenditure levels. I estimate equation (3) over two time horizons: A broad time horizon using data going up to 30 days before high-cost borrowers borrow for the first time, and a narrow time horizon, where I only use data that lies at least a year before high-cost borrowers borrow for the first time. This allows me to assess whether the estimated sensitivity is stable over time as it should be if it is indeed reflecting inherent personality traits. I restrain from using data from month 0 and onwards, where borrowers have started to borrow from high-cost credit companies. This is to avoid that inflow of high-cost credit biases the estimates. Lastly, to ensure that liquidity constraints do not drive the results, I (in line with Kuchler and Pagel (2021)) filter out weeks where individuals have very low levels of liquidity. I do this in a simplistic manner, and drop in the preferred specification, which is also reported in the main text, weeks where start-of-week balances are below 1,000 DKK. To gauge the importance of the liquidity threshold, I also report estimates with a 0, 5,000 and 10,000 DKK threshold.

The results of estimating equation (3) are presented in table E.1 below. The top panel shows estimates using the preferred specification with a liquidity constraint of 1,000 DKK. The estimates highlighted with bold font are the ones that are also included in table 2 in the main text. The three panels below show robustness estimates with liquidity constraints going from 0 to 10,000 DKK. Across all time horizons and definitions of short-run consumables, I find that high-cost borrowers appear more present-biased than all of the comparison groups. High-cost borrowers tend to have a paycheck sensitivity which is 30%-50% larger than the comparison group matched on age, gender, income and liquidity and close to double compared to the two comparison groups that are not matched on income or liquidity. Looking across the different panels, I find that while the size of the paycheck sensitivity is negatively correlated with the level of the liquidity threshold (meaning that the more liquidity I restrict the individuals to hold in the start of the week, the smaller is the paycheck sensitivity), the estimates only change modestly and the qualitative implications are unaffected. This reassures me that the findings are not driven by differences in liquidity constraints across the groups.

Table E.1: Kuchler-Pagel present-bias indicator - Paycheck sensitivity estimates

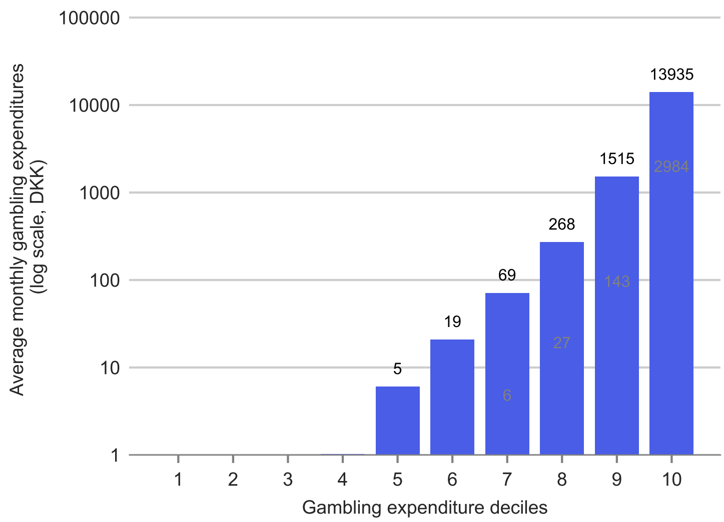
	Up to 1 month before		Up to 1 year before	
	Short-run consumables	Going out	Short-run consumables	Going out
Start-of-week liquidity above 1000 DKK				
High-cost borrowers	**42.3*** **	71.8***	40.7***	70.3***
	(0.6)	(1.2)	(0.8)	(1.5)
Matched age, gender, income & liquidity	**32.8*** **	60.1***	31.8***	57.2***
	(0.5)	(1.1)	(0.6)	(1.3)
Matched age & gender	**22.6*** **	43.7***	21.9***	42.5***
	(0.4)	(0.9)	(0.5)	(1.1)
Random sample	**21.4*** **	41.7***	20.8***	40.9***
	(0.5)	(0.9)	(0.5)	(1.1)
No liquidity restriction				
High-cost borrowers	69.1***	97.2***	65.7***	93.9***
	(0.7)	(1.2)	(0.9)	(1.5)
Matched age, gender, income & liquidity	51.4***	77.2***	49.6***	73.2***
	(0.6)	(1.1)	(0.8)	(1.3)
Matched age & gender	27.7***	48.9***	26.9***	47.6***
	(0.5)	(0.9)	(0.6)	(1.1)
Random sample	25.3***	45.4***	24.7***	44.6***
	(0.5)	(0.9)	(0.6)	(1.1)
Start-of-week liquidity above 5000 DKK				
High-cost borrowers	31.0***	56.1***	30.4***	56.1***
	(0.8)	(1.4)	(0.9)	(1.8)
Matched age, gender, income & liquidity	23.7***	47.0***	23.5***	44.8***
	(0.6)	(1.2)	(0.7)	(1.5)
Matched age & gender	19.8***	39.6***	19.2***	38.4***
	(0.4)	(0.9)	(0.5)	(1.1)
Random sample	18.9***	38.1***	18.5***	37.6***
	(0.5)	(0.9)	(0.5)	(1.1)
Start-of-week liquidity above 10000 DKK				
High-cost borrowers	31.1***	55.9***	30.6***	56.0***
	(1.0)	(1.8)	(1.2)	(2.2)
Matched age, gender, income & liquidity	22.2***	44.7***	21.7***	44.0***
	(0.7)	(1.4)	(0.9)	(1.8)
Matched age & gender	19.2***	38.6***	18.4***	36.9***
	(0.4)	(0.9)	(0.5)	(1.1)
Random sample	18.1***	37.2***	17.7***	37.0***
	(0.5)	(0.9)	(0.5)	(1.1)

The table shows estimates of γ_1 from equation 3. Each panel contains four rows, one for the high-cost borrowers and one for each of the three comparison groups. Standard errors are clustered at the individual level. The top panel shows results with a 1,000 DKK liquidity constraint threshold, meaning that all weeks where an individual's start of week liquidity is lower than 1,000 DKK are filtered away. The three other panels show results with similarly implemented liquidity constraint thresholds at 0, 5,000 and 10,000 DKK. The dependent variable is winsorized at the 1% level. The left two columns show results using observations going up to 30 days before high-cost borrowers first high-cost loan event. The two right columns show results using observations going only up to 365 days before high-cost borrowers first high-cost loan event.

F High-cost borrowers' gambling behaviour

In this section, I shed more light on the high-cost borrowers' gambling behaviour. I first investigate how prevalent gambling is among the high-cost borrowers. I do this by summing all gambling expenditures across the full sample window (i.e., from month -12 to month 6), and rank individuals in deciles of total gambling expenditures. The results of this exercise are shown in figure F.1. I find that around 40% of high-cost borrowers (the four lowest deciles) do not gamble at all. On the other hand, I find that the top decile in terms of gambling expenditures are gambling for close to 14,000 each month over this 19-month period. That adds ups to over a quarter of a million. The grey figures inside the bars in figure F.1 show the equivalent amounts for the comparison group matched on age, gender, income, and liquidity. This shows that while gambling is also widespread among consumers in general, the magnitude of the high-cost borrowers' gambling is extraordinary.

Figure F.1: High-cost borrowers' average monthly gambling expenditures, month -12 to 6

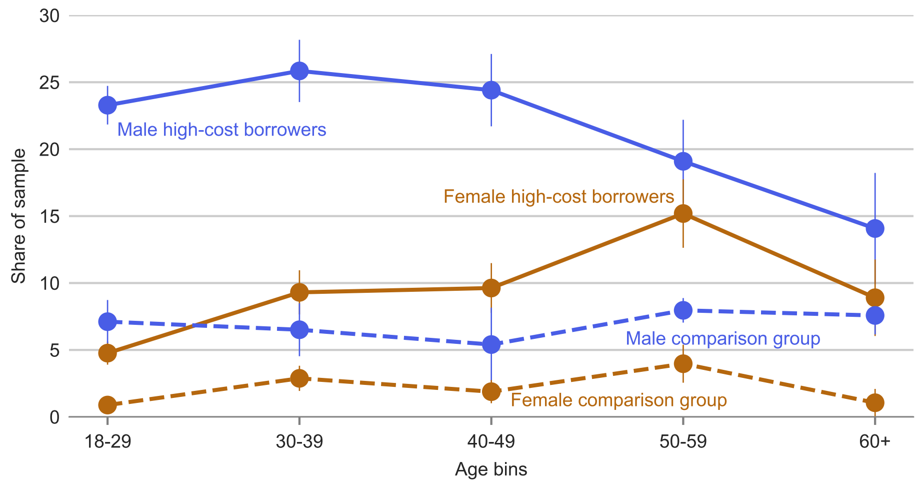


The plot shows average monthly gambling expenditures by deciles of total gambling expenditures evaluated over the full sample period from month -12 to month 6. Note that the scale is log-transformed. The grey figures show the corresponding amounts for the comparison group matched on age, gender, income and liquidity.

Gambling is often thought of as a "young male" phenomenon, with much gambling being associated with sports betting. To see whether this is true, I explore the age and gender distribution of "gamblers"[38] in figure F.3. I confirm that it is especially the male high-cost borrowers that are gambling a lot. Around 25% of the male high-cost borrowers between 18-50 years gamble for at least 1,000 per month over the 19-month period. For the men in the comparison group, the corresponding figures are below 10%. For women, I find a smaller but still significant difference between the high-cost borrowers and the comparison group. Also, female high-cost borrowers exhibit a positive age gradient, while the opposite is the case for the male high-cost borrowers. This means that for the high-cost borrowers aged 50 or older, there is no statistical difference in gambling prevalence between men and women.

[38] I define "gamblers" as individuals whose average monthly gambling expenditures exceed 1,000 DKK over the full 19-month sample period.

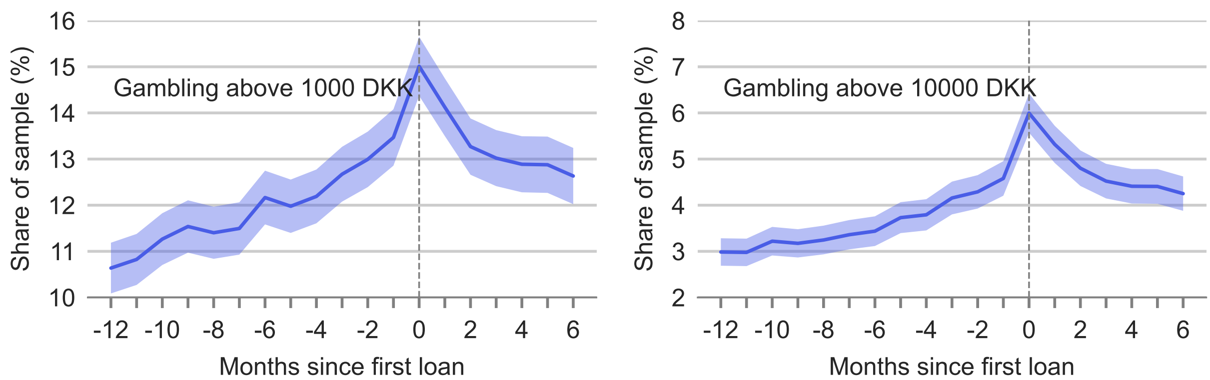
Figure F.2: Age- and gender distribution of high volume gamblers



The plot shows by group (i.e., high-cost borrowers and comparison group), age and gender, how large a share that is gambling for more than 1,000 DKK on average each month over the full sample period from month -12 to month 6. The bars indicate 95% confidence intervals, based on robust standard errors.

Lastly, in figure F.3, I explore the evolution in the share of high-cost borrowers who are high-volume gamblers around the first high-cost loan event. I define two binary outcomes: Monthly gambling expenditures above 1,000 DKK and monthly gambling expenditures above 10,000 DKK. For the former, I find that close to 11% of the high-cost borrowers are gambling for more than 1,000 DKK 12 months before they borrow for the first time. This share grows almost linearly until month -1 to around 13%. From month -1 to 0 it jumps with an additional two percentage points to 15%. This shows that the evolution in gambling found in figure 3 is not just driven by the same individuals increasing their gambling amounts. Instead, it is an increasing number of individuals who gamble for substantial amounts. In the right panel, I find the same picture for "extreme gambling" (i.e., gambling for more than 10,000 DKK in a month). Going from month -12 to 0, the share of individuals who are gambling at an extreme level doubles, from 3 % to 6%.

Figure F.3: Evolution in share of high-volume gamblers, month -12 to 6.



The plot shows the evolution in the share of individuals who are gambling for more than 1,000 DKK in a month (left panel) and for more than 10,000 DKK in month (right panel) for the group of high-cost borrowers. The figures are predicted values based on equation 1, with all other variables than event time fixed at sample averages. Outcomes are winsorized at the 99.9% level. Shaded area indicate 95% confidence intervals, based on robust standard errors.