Short-term consumption patterns between financially exposed and robust individuals: Impact of interest rate changes during and after COVID-19

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Abstract

Employing administrative data on mortgagers from a Norwegian bank, we examined the role of financial robustness in consumption responses. We took advantage of the sudden interest rate cut caused by the COVID-19 pandemic in the spring of 2020 and the subsequent interest rate increase during the winter of 2021-22. We employed a difference-in-differences research design to compare financially robust and exposed individuals, measured by their loan-to-value ratio relative to their age group. We estimated the level of heterogeneity between the two groups in terms of their short-term consumption responses to interest rate changes. During the interest rate hike period, we found no significant differences in consumption development between the two groups. This is not in accordance with the cash flow channel and is asymmetric with the results following the interest rate-cut. In addition to the cash flow channel, we highlight the effect of risk-aversion heterogeneity, under which precautionary savings and substitution channels are plausible explanatory factors. The primary contribution of this study lies in the approach used on a novel dataset to examine the short-term consumption responses to interest rate changes. Finally, this study provides a useful foundation for future studies. Increased knowledge about the heterogeneity in short-term consumption responses to interest rate changes may have implications for monetary policies.

Keywords: mortgagers, interest rate changes, private consumption, financial exposure, cash flow channels

JEL codes: E21, E52, D12

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1 Introduction

Understanding the channels through which interest rates affect private consumption is essential to properly explain the transmission mechanisms of monetary policies. This study analyzes the short-run heterogeneity responses in consumption following interest rate changes. Specifically, we estimate the effect of financial robustness on heterogeneity.

We hypothesize that financially-exposed individuals change their consumption more following an interest rate change than financially-robust individuals would. This is in line with the theoretical cash flow channel, which describes how interest rate changes impact interest expenses or income changes, and consequently, disposable income, which again impacts consumption. Individuals with different levels of indebtedness experience varying disposable income effects. This suggests heterogeneity in the consumption responses among individuals with different levels of indebtedness. In Norway, where the average household has more debt than liquid assets, the cash flow channel strengthens monetary policy such that an interest rate hike further decreases aggregate demand.

The long-term effects of the cash flow channel have been thoroughly researched using administrative register data, and several studies show significant differences between how financially exposed and robust groups adapt to interest rate changes. However, research focusing on short-term heterogeneous effects is rare, owing to insufficient data access. We offer an alternative and novel approach using microdata on monthly observations from the BN Bank, a small nationwide Norwegian bank, to estimate the short-term effects of interest rate shocks on heterogeneity in consumption.

This study of analyzing heterogeneous short-term interest effects on private consumption using administrative data from a bank is rare in the existing literature. Our dataset is novel because it has not been previously employed to conduct a macroeconomic analysis of financial vulnerabilities. Moreover, we analyze both interest rate cuts and hikes and investigate whether the consumption differences between the groups (financially exposed vs robust) in response to interest rate changes are symmetric to interest rate cuts and hikes. Bank data are scarcely accessible for research, making our contributions even more valuable.

In the Norwegian context, research on short-term effects is particularly interesting because almost all households have variable-rate mortgages (VRMs) (Statistics Norway, 2023e). Therefore, the short-term effect of interest rate changes should be more important than in comparable countries where a larger share of debt is in fixed-rate mortgages (FRMs) or adjustable-rate mortgages (ARMs). Understanding the swiftness with which interest rates affect the real economy is important. Therefore, we must understand short-term consumption responses to interest rate changes. Almost all the research on this topic in comparable countries uses administrative register data with yearly observations, preventing them from studying shocks in the short term. The contribution of this study is to investigate short-term consumption responses to interest rate changes and discuss whether an approach using monthly bank data is fruitful for these types of analyses.

The remainder of this paper is structured as follows. We shall present the background of the debt situation in Norway and the economic implications of COVID-19. We then follow with a section on the theoretical framework and literature, in which we present key studies for our analysis. Furthermore, we present the data employed for the analysis, accompanied by descriptive statistics. The subsequent section presents our empirical strategy, with an emphasis on the choice of method, treatment group, and period. Next, we present the results, followed by closely related robustness checks. The results form the basis for the discussion section, in which we draw parallels between our results and the economic theory.

2 Background

2.1 The Indebtedness in Norway & Macroprudential Regulations

In line with the low interest rates and rising housing prices since the early 2000s, indebtedness among Norwegian households has increased significantly (Norges Bank (2023); Figure 1). Households' average debt-to-income (DTI) ratio has surged well above 200%, placing Norway as the second most indebted OECD country after Denmark (OECD, 2023). High indebtedness is closely related to a high homeownership rate (Figure 2). As of 2022, households' new installment loans had an average loan-to-value (LTV) ratio of 64% and a DTI ratio of 347% (Finanstilsynet, 2022a)[1]. In contrast to the prevalence of FRMs and ARMs in Denmark and many other countries, VRMs[2] are predominant in Norway (Statistics Norway, 2023e)[3]. The large share of VRMs provides a rapid pass-through from changes in the central bank's policy rate to household interest expenses, making Norwegian households particularly vulnerable to interest rates and income shocks (Gulbrandsen, 2023). These circumstances have raised concerns about financial stability and the potential negative consequences of economic crises. One cause of concern is that households might cut their expenses more than they would normally during an economic downturn (Finanstilsynet, 2022b, p. 7; Norges Bank, 2022b, p. 7)[4]. However, the high share of VRMs also means that the policy rate may be a more efficient tool in Norway than in comparable countries owing to the swiftness of pass-through effects.

Macroprudential regulations were gradually introduced in Norway after the Great Recession to reduce debt accumulation among at-risk households. Since its introduction in 2011, the regulations have been amended multiple times. As elaborated by Finans Department et al.(2022)[5], lending regulations impose limitations on banks' lending practices and include several borrower requirements. Borrowers are allowed a maximum LTV ratio of 85%, with the required principal payments for loans exceeding 60% in LTV ratio. Second, the DTI ratio cannot exceed 500%. Borrowers must also be able to withstand the interest rate stress test of debt serviceability. From January 2023, this stress test requires households to manage an interest increase of 3% and a minimum rate of 7%. This adjustment loosened the previous requirement of withstanding a 5% increase. Additionally, there is a flexibility quota, which is the share of the capital volume of loans in each quarter; this allows banks to deviate from the requirements. From July 2023, the regulations will cover mortgages and loans with other collateral (Finansdepartementet, 2022).

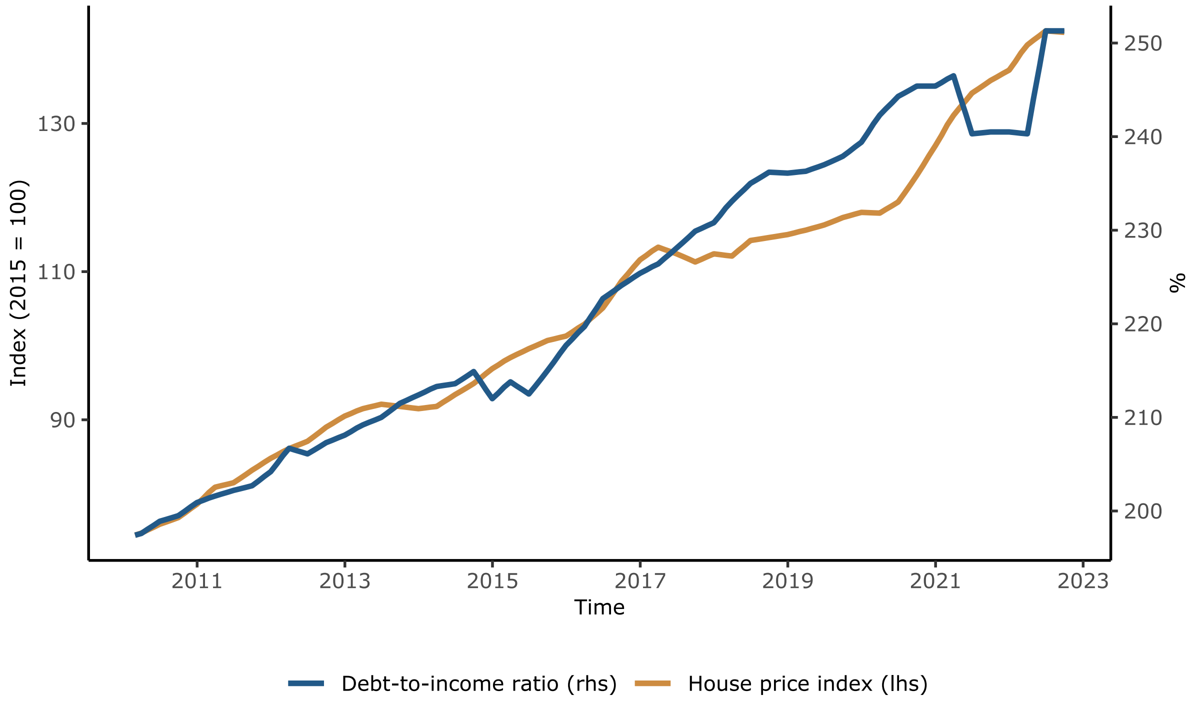
[1] Finanstilsynet is the Financial Supervisory Authority of Norway.

[2] We distinguish between adjustable-rate, fixed-rate, and variable-rate mortgages. VRMs have a variable-rate over all of the loan's term, as apposed FRMs in which the interest rate remains the same. ARMs employ an initial period with a fixed-rate, followed by variable-rate that resets regularly (Hayes, 2022).

[3] Statistics Norway (Statistisk Sentralbyrå) is the Norwegian statistics bureau.

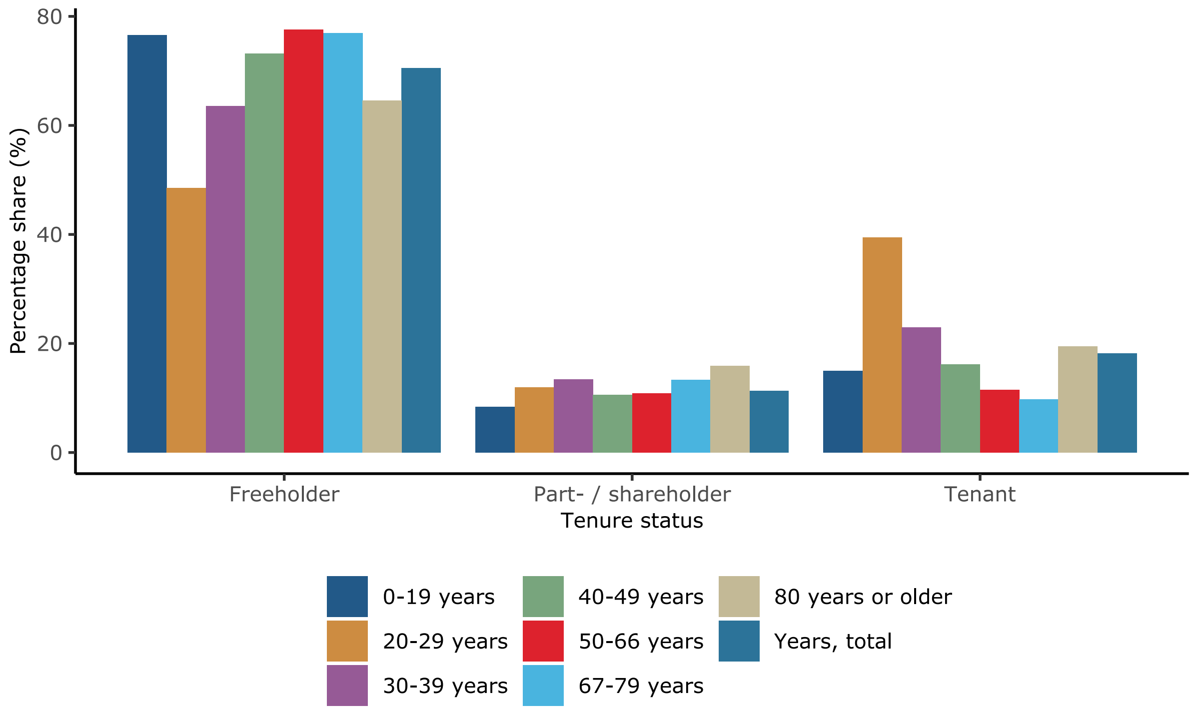
[4] Norges Bank is the central bank of Norway.

[5] Finansdepartementet is the Norwegian Minstry of Finance.



Seasonally Adjusted Debt-to-Income Ratios Retrieved from Statistics Norway (2023d).
Seasonally adjusted price indices of existing dwellings. Retrieved from Statistics Norway (2023b).

Figure 1: Development of Housing Prices and Indebtedness Level in Norway



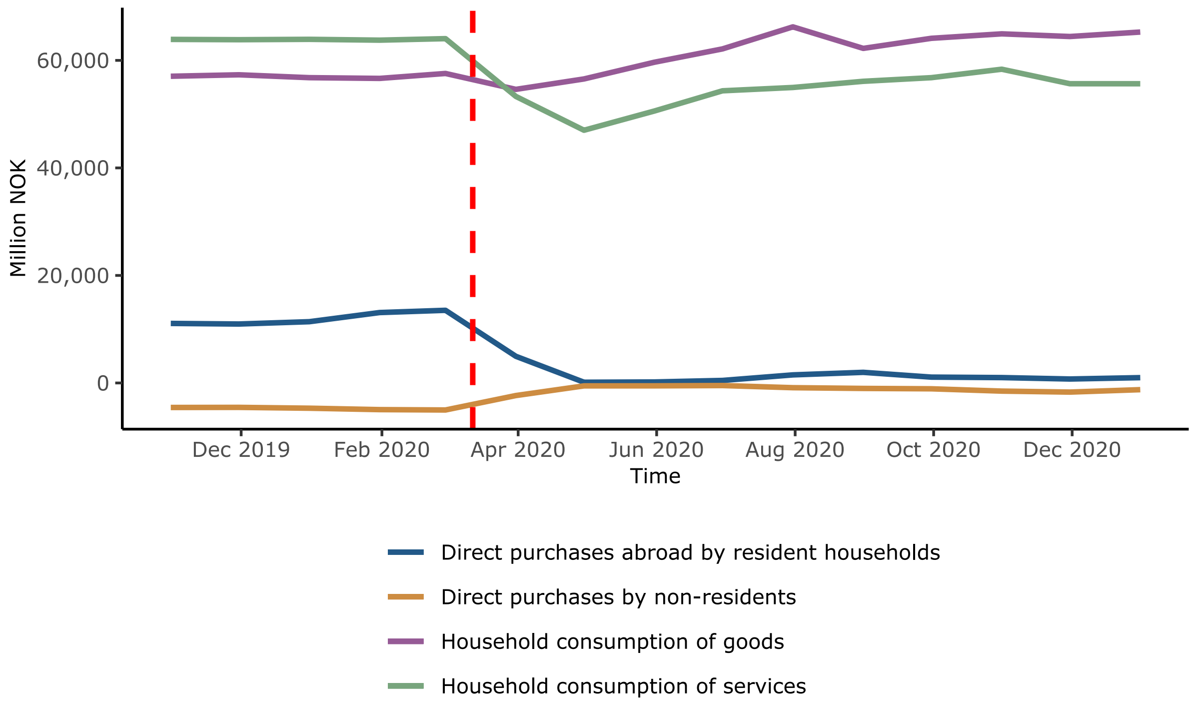
Tenure status for all dwellings in the entire country in 2022. Retrieved from Statistics Norway (2023 g).

Figure 2: Home Ownership Rates in Norway

2.2 The COVID-19 Pandemic and Monetary Policy Responses

The COVID-19 pandemic has caused an upheaval in the global economy, resulting in the most severe global economic crisis of more than a century (World Bank 2022, p. 25). Both the interest rate cut and hike periods were marked by the pandemic and its associated economic consequences, severely affecting household consumption.

The first period we analyze is the interest rate-cut period from December 2019 to May 2020. In response to the onset of the pandemic, the Norwegian government imposed a national lockdown on March 12, 2020, to prevent infections and protect public health. The lockdown entailed significant economic consequences characterized by reduced economic activity, increased unemployment, and interest rate cuts (Koronakommisjonen, 2021). Restrictive infection control measures meant that people had to stay at home, limiting their ability to purchase. The aggregate household consumption sharply declined in March and April, but spending on goods recovered rapidly. As Koronakommisjonen (2022) [6] describes, these measures particularly affected service industries, which adapted poorly to social-distancing requirements. Tourism-related industries were also hit hard. From 2019-2020, the total household consumption fell by 6.3%, driven by a decrease in the consumption of services. Households shifted their consumption from services to goods, but an increased share also went into savings (Statistics Norway, 2023h). According to calculations by Brasch et al. (2022), the decline in economic activity caused a decrease in mainland GDP of 4.7%, compared to a counterfactual scenario without a pandemic.



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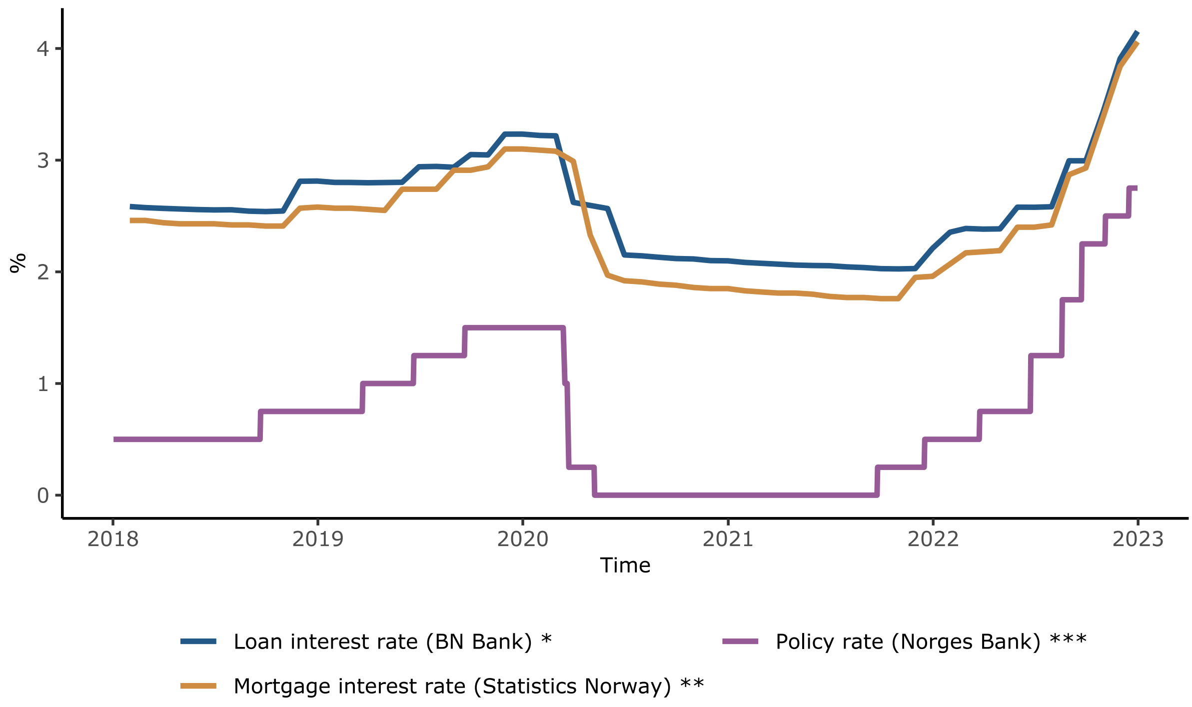
[6] Koronakommisjonen, the Coronavirus Commission, is an independent commission appointed by the government to conduct a thorough and comprehensive review and draw lessons from the COVID-19 outbreak in Norway.

Household total consumption expenditure. The 2020 prices are adjusted seasonally.
Retrieved from Statistics Norway (2023h).

Figure 3: Expenditure Development During the COVID-19 Pandemic

Monetary policy actions were conducted rapidly to counteract the negative economic shocks. As an immediate response to the national lockdown on March 12, Norges Bank reduced its policy rate from 1.5% to 1.0% the following day (Figure 4). One week later, on March 20, the central bank reduced its policy rate by 75 basis points. These measures caused abrupt interest-rate shocks to the economy. Commercial banks responded swiftly by lowering their lending rates faster than the standard notice period of six weeks. The mortgagers analyzed in this study rapidly received a cut in their loan interest rates of approximately 60 basis points. However, a full pass-through of the policy rate cut to loan interest rates took several months (Figure 4). Central banks also employed unconventional monetary policies, as stated by Olsen (2020). To improve its market liquidity, Norges Bank eased its collateral requirements[7] and issued extraordinary loans to commercial banks. Furthermore, it intervened in the foreign exchange market to ensure the stability of the krone (NOK).



* Mean loan interest rate on mortgages, home equity loans, and equity release mortgages in BN Bank. Monthly observations.
** Households' mortgage interest rate from Statistics Norway (2023f). Applies to outstanding repayment for loans secured on dwelling in total.
Floating interest (up to 3 months). Monthly observations.
*** Interest rate on banks' overnight deposits in Norges Bank. Daily observations.

Figure 4: Development in Interest Rates

The second period, the interest rate hike period, was the onset of a series of interest rate hikes during the pandemic. This period extends from September 2021 to March 2022. On September 24, 2021, the Norwegian Government decided that Norway would move towards normal everyday life, lifting the vast majority of infection control measures (DSS, 2022). On the same day, after 15 months with a zero-policy rate, the central bank increased its policy rate to 0.25%. This hike was in line with forward guidance from

[7] Collateral requirements involves the countercyclical capital buffer rate for the banks which was eased from 2.5% to 1% in March 2020 (Norges Bank, 2022a).

the central bank (Norges Bank, 2021a, p. 42; 2021b, p. 48) and thus expected by the market. A further 25 basis point increase in the policy rate was initiated on December 17. Norges Bank has continued to increase gradually, reaching a policy rate of 3.25% as of May 2023 (Norges Bank, 2023). The first transmission of the policy rate to the mortgagers was analyzed in December and January, when the bank loan interest rate increased by approximately 30 basis points.

Overall, during both the interest rate cut and hike periods, there was significant macroeconomic news apart from interest rate changes. These events have contributed to monetary policy actions. As such, other factors contributing to fluctuations in private consumption besides the interest rate fluctuations are focused in this study.

3 Theoretical framework and literature review

In this section, we highlight traditional lifecycle hypotheses. Next, we present a standard two-period macroeconomic consumption model and describe how interest rates affect consumption. Furthermore, we emphasize the importance of considering individual risk tolerance heterogeneity when analyzing consumption responses. We also review previous research, focusing on the most relevant papers and the cash flow channel of interest rate changes.

The cash flow channel, according to several studies (Di Maggio et al., 2017; Jappelini and Scognamiglio, 2018; Flodén et al, 2021) is a significant channel for monetary policy transmission. According to traditional macroeconomic policy, the interest rate changes on consumption are only affected by the substitution effect through intertemporal substitution. The effect will only be as large as that when the new interest rate changes the equilibrium of the Euler equation optimization problem.

In the cash flow channel, consumption interest rates affect individuals' disposable income either through changed interest payments or income, depending on their level of net assets (Flodén et al., 2021).

In Norway, where the vast majority of mortgagers have VRMs, the cash flow channel would rapidly impact mortgagers shortly after the central bank changes its policy rate. In the context of our dataset, the cash flow channel suggests that financially exposed groups would change their consumption more than financially robust groups would when faced with loan interest-rate changes. This is due to differences in indebtedness indicating that disposable income shocks will be greater for the exposed group when the interest rate changes.

In a situation where access to credit is limited and knowledge about future interest rates and income is not perfect, individuals may change their consumption curve more than the intertemporal substitution prediction indicating that significant cash flow effect.

3.1 Heterogeneity in Individual's Risk Tolerance

Studies by Sahm (2012) and Bonin et al. (2007) indicate that factors such as age, gender, income, occupation, and personal experience can significantly influence risk tolerance and hence consumption behavior.

Sahm (2012) underlines the positive relationship between the business cycle and risk taking, which is undeniable. Economic upturns increase risk taking among individuals. Because the risk profile of individuals is related to how precautionary they are, Sahm's findings are relevant to buffer-stock behavior.

Several studies highlight key differences in individuals' risk preferences. Croson and Gneezy (2009) state that women tend to be more risk-averse than men. Bonin et al. (2007) explore individuals' choice of occupation, finding that individuals with high risk tolerance more often choose occupations with high earnings risk, which predominantly exists in the private sector.

3.2 Previous Research on the Cash flow channel

Several earlier studies have investigated the cash flow channel of interest rates using microdata. Di Maggio et al. (2017), Flodén et al. (2021), and Holm et al. (2021) show that individuals with lower liquid assets and higher debt tend to respond more strongly to interest rate changes. However, few studies have used Norwegian data, where the prevalence of VRMs is very high (Statistics Norway, 2023e). Studies that focus on short-term shocks are limited.

Di Maggio et al. (2017) find support for the cash flow channel in durable consumption, measured as the change in car consumption. Furthermore, they show that a higher level of voluntary deleveraging weakened this effect. They also show significant heterogeneity in the cash flow channel, with more liquid households having lower marginal propensity to consume (MPC) toward new cars. Instead, these individuals spend more of their increased disposable income on voluntary deleveraging than those with lower levels of liquid assets.

Flodén et al. (2021) estimate the cash flow channel using Swedish administrative registry data. They find that debt holders decreased their spending by 0.23 percentage points (to 0.55) more than non-debt individuals in response to a one-percentage point increase in the interest rate. They also find significant differences in the consumption response to interest changes between ARM and FRM holders and that those with low levels of liquid assets responded more strongly than those with high levels (ibid).

Gerdrup and Torstensen (2018) and Holm et al. (2021) estimate the cash flow channel using Norwegian data and found that the cash flow channel has strengthened during the past 15 to 20 years in accordance with higher debt levels, but that the strengthening has been slightly smaller than expected given debt development. This is because households possess more liquid funds than earlier. Holm et al. (2021) estimate the cash flow channel using Romer and Romer's (2004) method to estimate exogenous interest rate shocks. They perform a similar study to Flodén et al. (2021), but on Norwegian data, and find a significant cash flow channel and that households with different levels of liquid funds have different MPCs. Their results point in the same direction as those of Fagereng et al. (2021), who find that the MPC among lottery winners is larger among households with low levels of liquid funds.

Druedahl et al. (2022) notably suggest that households unlikely to have liquidity constraints increase their consumption when informed about an interest rate change, but not when the actual cash flow effect hits. However, households that are likely to be liquidity constrained increase their consumption when the cash flow effect hits and not when notified about the future interest rate change.

4 Data

In this section, we present the data employed for our analysis, how we filtered and manipulated it, and further details of the essential aspects of the data.

4.1 Data description

The data employed for the analysis are taken from a panel of mortgagers in BN Bank, a nationwide commercial bank. The bank is an Internet-only bank with a total retail lending of approximately 30 billion NOK and a current customer base of 101,000, of which 15,000 have mortgages (BN Bank ASA, 2023). The bank's customer portfolio is spread throughout Norway, but is predominately based in southeastern Norway (Figure 7). The panel spans from 2010 to late 2022, with a total of 1.8 million observations from 30,000 individuals with mortgages. The panel contains a range of variables describing essential demographic characteristics, loan-specific features, and consumption. Loans include mortgages, home equity loans, equity-release mortgages[8], and previously unsecured consumer credit[9]. Preparing the raw data for our purpose requires extensive data manipulation. Each customer was pseudonymized according to strict privacy considerations of the bank.

Table 1 shows descriptive statistics for the entire sample during the two periods of interest. The difference in mean consumption between the two periods is significant, with means of 14,500 NOK and 16,400 NOK during the cut and hike periods, respectively. As discussed in Section 2.2, the COVID-19 pandemic is likely the most dominant reason for the difference, as consumption during the interest rate cut period was particularly restricted. Additional factors of importance are seasonal effects, and, to some degree, inflation. The difference in deposit levels between the periods is also noticeable. One likely reason for this is that an accumulation of savings took place throughout the COVID-19 pandemic. The sample during the interest rate hike period is larger than that during the interest rate cut period. This is partially because the former period is a month longer and also because of an influx of new customers to the bank between the two periods. The influx of new customers may also have affected the level of deposits if the individuals entering the bank had high levels of deposits. However, this is speculative, and we do not know for sure.

[8] Equity release mortgages, available to customers aged 60 and above, enables them to release the equity in their property while retaining ownership. The funds can be disbursed as a lump sum or as recurring monthly payments, with no interest or instalment obligations for the recipients. The released funds can be utilized for any desired purpose.

[9] The issuance of unsecured consumer credit in the bank was initiated in 2016 and discontinued in 2019.

Table 1: Descriptive Sample Statistics

	Interest rate cut period (N=1580)	Interest rate hike period (N=2065)
Consumption (NOK)		
Mean (SD)	14,500 (± 7,300)	16,400 (± 7,900)
Median [Min / Max]	14,000 [0 / 39,200]	15,600 [0 / 42,300]
Deposits (NOK)		
Mean (SD)	155,300 (± 297,500)	224,900 (± 436,600)
Median [Min / Max]	49,600 [-100 / 4,075,500]	75,600 [0 / 7,084,800]
Loan interest rate		
Mean (SD)	2.91 (± 0.39)	2.15 (± 0.34)
Median [Min / Max]	2.85 [1.48 / 4.9]	2.09 [0.89 / 3.51]
LTV ratio		
Mean (SD)	0.51 (± 0.27)	0.46 (± 0.26)
Median [Min / Max]	0.62 [0.04 / 0.86]	0.45 [0.03 / 0.86]
Loan size (EAD)		
Mean (SD)	2,273,900 (± 1,566,800)	2,363,300 (± 1,693,000)
Median [Min / Max]	2,087,900 [29,600 / 9,976,500]	2,051,500 [41,600 / 9,817,900]
Large buffer (1 = yes)		
Mean (SD)	0.26 (± 0.44)	0.35 (± 0.48)
Median [Min / Max]	0 [0 / 1]	0 [0 / 1]
Debt expander (1 = yes)		
Mean (SD)	0.06 (± 0.24)	0.07 (± 0.25)
Median [Min / Max]	0 [0 / 1]	0 [0 / 1]
Occupation		
Private sector	945 (60 %)	1187 (57 %)
Public sector	265 (17 %)	299 (14 %)
Retired	206 (13 %)	349 (17 %)
Self-employed	41 (3 %)	55 (3 %)
Missing	123 (7.8%)	175 (8.5%)
Co-dependent (1 = yes)		
Mean (SD)	0.56 (± 0.5)	0.56 (± 0.5)
Median [Min / Max]	1 [0 / 1]	1 [0 / 1]
Age (years)		
Mean (SD)	51.29 (± 12.57)	52.9 (± 13.65)
Median [Min / Max]	50 [26 / 92]	52 [26 / 93]
Gender		
Female	601 (38 %)	748 (36 %)
Male	979 (62 %)	1317 (64 %)
Large Urban Area (1 = yes)		
Mean (SD)	0.74 (± 0.44)	0.74 (± 0.44)
Median [Min / Max]	1 [0 / 1]	1 [0 / 1]

Note:
See the appendix for a complete description of the variables.
Total includes control and treatment groups.
Computed on the sample before matching.
Interest rate *cut* period based on the period from December 31, 2019, until May 2015, 2020.
Interest rate *hike* period based on the period from September 30, 2021, until March 31, 2022.
Continuous values greater than 1,000 are rounded to the nearest hundred, while values that are less are rounded to the nearest two decimal places.

4.2 Data Manipulation

Forbrukerrådet (2023, p. 33) found that over half of Norwegians have multiple banking relationships. Thus, we limited the dataset to active spenders, preferably their primary banks. BN Bank offers only high-interest savings accounts due to its small size and focus and does not offer mutual fund savings; therefore, investors must look elsewhere. Thus, some BN Bank customers spend and save money on unobserved banks.

We set some exclusion criteria for customers unlikely to use BN Bank as their daily spending bank because their activities in other banks are unknown. We excluded observations with monthly spending of less than 5,000 NOK and fewer than five card transactions. It was impossible to accurately identify the desired individuals, which limited the sample size.

As serial loan customers are rare, they may behave differently from annuity customers. We also required pre- and post-treatment customer observations; this prevents banking relationship disruptions. Two periods are required to define the Debt Expander control variable, which depends on the relative change between periods. Setting lower and upper fences eliminated extreme consumption. Subtracting 1.5 from the first quartile yielded the lower limit. The upper limit was 1.5 times the third quartile.

Some panelists, usually self-employed, held large business loans. We excluded people with loans over 10 million NOK (the 99th percentile) to avoid non-private behavior distorting the results.

The current county and municipal names were used to avoid issues with the 2020 regional reform. The postal location, which was mostly unaffected by the regional reform, helped distinguish between those whose municipality or county changed names and those who moved. Residential data determined whether customers live in large urban areas, which is an important control variable. Not correcting for the interest rate-cut period, when most regional changes were implemented, could have consequences.

4.3 The Consumption Measure

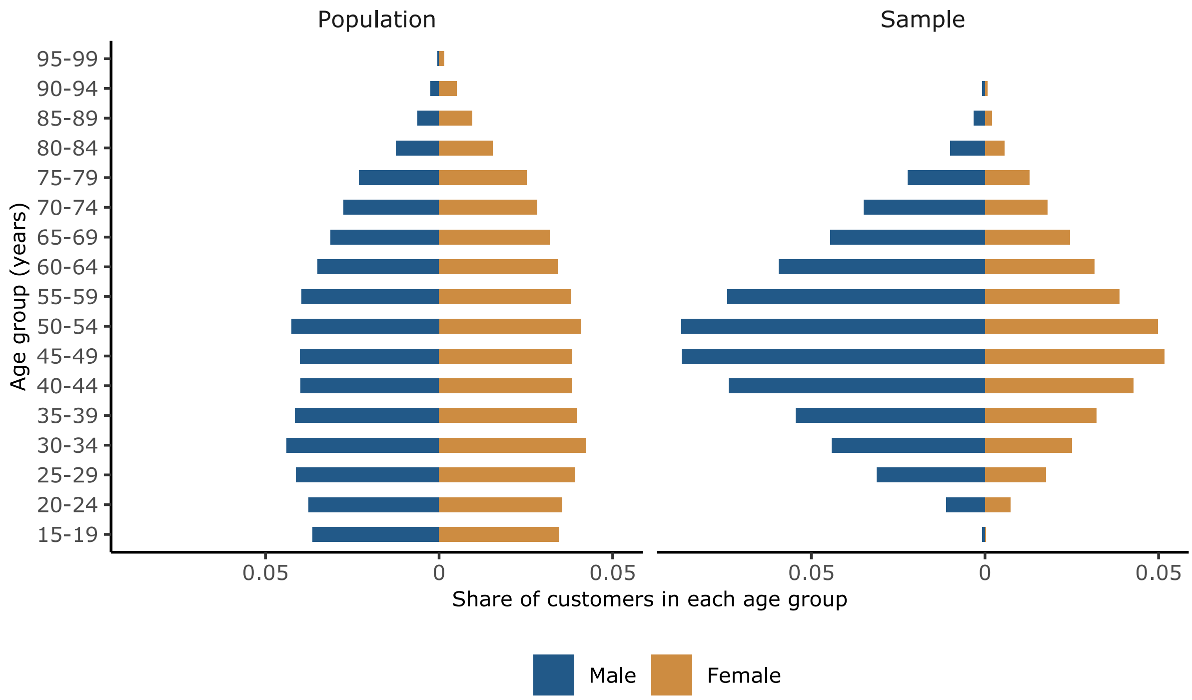
Our key variable of interest-consumption-captures debit card transactions and cash withdrawals. As the consumption variable is an aggregate measure, we cannot observe granularity in individual consumption. A common approach in the literature is to distinguish between the consumption of goods and services and the consumption of durables and non-durables. Consumption measures failed to make these distinctions, resulting in some implications.

Furthermore, Black and Cusbert (2010) suggest that the consumption of durables is more closely correlated with the economic cycle than that of non-durables, as one can often postpone purchasing these goods during challenging economic times. Nor does the consumption variable capture a significant part of the consumption of durable goods, as people often purchase these goods through wire transfers rather than card payments.

A common approach adopted in other studies is to use register data with complete information. Registry data allow individuals to cluster at the household level and observe household consumption, in which case it does not matter whose name is on the mortgage. Additionally, studies using data with complete information have the advantage of allowing scholars to use accounting identities to obtain a full overview of consumption. When using register data, one can observe an individual's full balance sheet; hence, there is no error in the consumption measure. Access to register data also allows researchers to calculate a more precise MPC because they have a complete overview of household income.

4.4 Representativeness of sample

This section discusses the representativeness of the sample, which differs from the general Norwegian population in several respects. Because we were analyzing mortgagers, certain age groups were overrepresented. The age distribution in our sample differed from that of the general population. The age distribution of the BN Bank customer portfolio is centered on the middle-aged population. Observing this age distribution is natural because people typically take on their first loans in the establishment phase of life and amortize them as they age. Furthermore, the sample was skewed in favor of men. The gender gap in the sample may have several explanations, but men are predominantly the main borrowers in banks. This pattern is also prevalent among other banks (Lycke, 2020). Hence, our sample is representative of a general mortgage.



Sample: Distribution of mortgages in BN Bank in 2020.
Population: Distribution of the entire population in 2023. Retrieved from Statistics Norway (2023c).

Figure 5: Population Pyramid

BN Bank is a nationwide bank, but its customers are mostly from southeastern Norway (Figure 7) and live in large urban areas (Table 2). As individuals choose the bank they use, the sample may have selection issues. The customer mass of banks is not randomly chosen but is related to the type of products the bank offers and their pricing, marketing, and strategy. As BN Bank is an Internet-only bank, individuals from the whole country have access to the bank, but southeastern Norway is a target area for the bank.

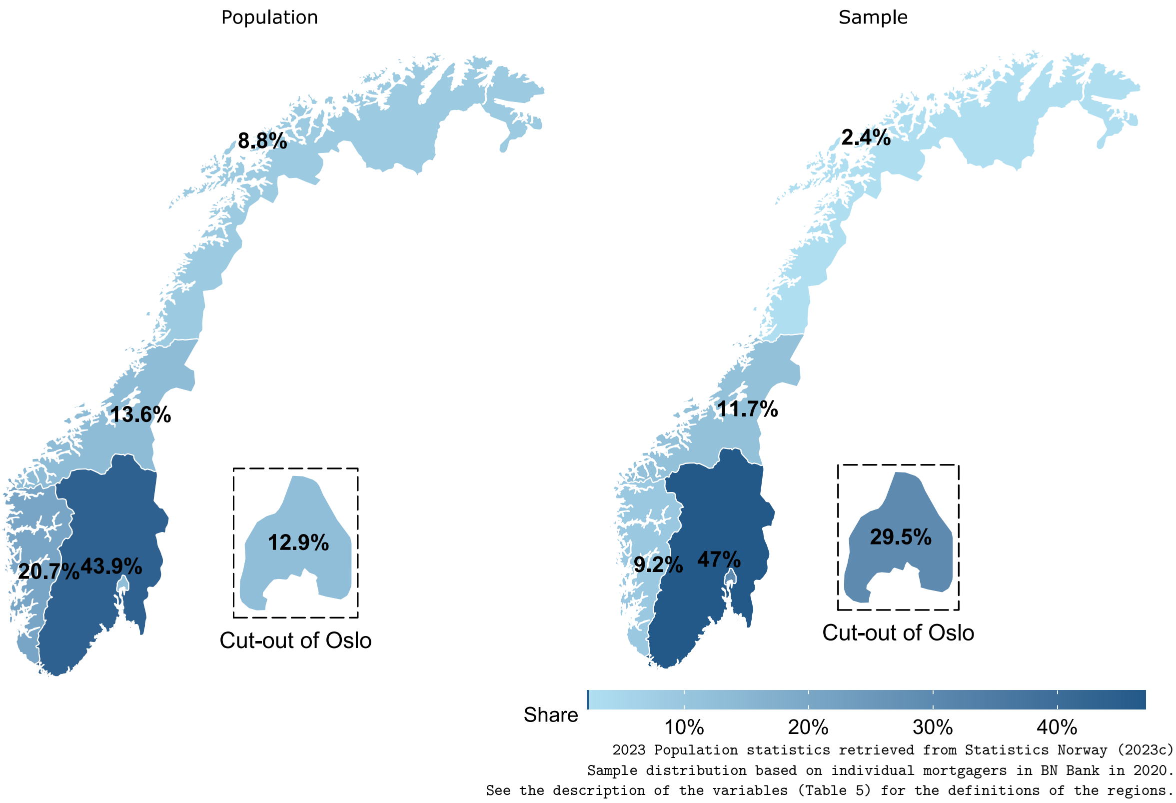


Figure 6: Regional Distribution

4.5 Control Variables

A series of control variables were included in the analysis. This section explains the control variables and their definitions. We discuss the rationale for introducing each control in Section 5.6. Further details on the variables are provided in the variable description (Table 5).

First, we controlled for demographic variables, including sex and retirement status. As we did not directly observe which customers were retired, we defined them as *Retired* if they were older than 67 years. Additionally, we created a dummy variable, *Large Urban Area,* indicating whether an individual resides in an urban settlement with more than 100,000 inhabitants. These areas include the largest cities and surrounding municipalities where the settlement is considered contiguous[10] (Statistics Norway, 2023a).

Several loan-specific controls are included. We defined a dummy variable, *Large Buffer,* based on customers' deposit holdings, which include checking and savings accounts. It comprises individuals with deposits larger than 200,000 NOK, which corresponds to the highest quintile. Furthermore, we defined a dummy variable for individuals who expanded their debt from pre-treatment to post-treatment periods. By examining the relative change in the average debt between the two periods, we identified individuals as *Debt Expanders* if their debt increases by more than 1%. This increase in borrowing can occur through mortgages, home equity loans, or equity-release mortgages.

[10] See the variable list in appendix (Table 5) for details on included municipalities.

Moreover, we defined the dummy variable *Co-dependent,* indicating whether an individual has a co-borrower of their mortgages. Both borrowers are joint co-owners of the property, and are equally obliged to repay the mortgage. In Norway, a loan with two or more borrowers is established such that it is registered in the main borrower's account. As a result, coborrowers who do not have loans registered in their accounts are excluded from our dataset. It was not possible to link the main borrowers and co-borrowers, preventing us from clustering individuals at the household level. We did not identify customers who had a co-signer on their mortgages. Co-signers provide collateral and are obliged to repay the loan but are not co-owners of the property. Typically, co-signers are parents who help their children purchase their first home.

The dataset also contained data on loan applications. Here, more detailed information on the household structures was gathered. For instance, income, family structure, and other important parameters were observed. Furthermore, these data are seldom retrieved because they are only collected in connection with alterations to existing loans or applications for new loans. Consequently, the accuracy of the variables gathered from the loan applications is questionable, and we did not employ them during the analysis.

5 Method

In this section, we discuss the empirical strategy of the DiD approach, followed by the choice of treatment groups and the timing of treatment. Additionally, we discussed the heterogeneity between the groups. Finally, we present the model and its specifications.

5.1 Empirical Strategy

Our empirical strategy is based on the DiD approach. This method allows us to isolate the heterogeneous responses to an interest rate shock between the financially robust and exposed groups, given that the two groups would be subject to parallel trends with no shock. The assumption of parallel trends is essential for the DiD analysis.

We simplified our dataset into a setup comprising two periods and two groups. This setup enables us to use time-invariant control variables (most of our controls are) and measure the average treatment effects at the group level. By conducting a DiD analysis, we do not estimate individual-level consumption responses to interest shocks as in traditional panel methods. Instead, we measured general responses at the group level between financially exposed and robust.

Individual-level fixed-effects models have trouble isolating individuals' responses to interest rate changes through consumption from other economic effects. One such effect is seasonal variation, which is so large that it outweighs the estimated effect. Given the size of the panel and the emphasis on short-term effects in this study, we would also run into the problem of losing many degrees of freedom. More precisely, we would lose approximately one-sixth of the degrees of freedom in the dataset when analyzing a six-month period with individual-level panel data instead of splitting the individuals into two groups.

In absolute terms, the effect of changed interest rates on disposable income depends on loan size, the number of periods until default, and other indicators such as the freedom of installments. The relative effects depend on the LTV and DTI ratios. The DTI ratio in our dataset was mostly based on outdated observations and was not a reliable measure. Therefore, we used the LTV ratio as a relative measure. A relative measure of indebtedness is preferred to measure financial robustness, as individuals with higher income and wealth often have larger loans. However, this does not necessarily mean that they are more financially exposed, because they have higher incomes and wealth.

5.2 Choice of Treatment Group

Several endogeneity challenges are associated with traditional measurements of financial exposure. The size of the loan and the LTV ratio are heavily correlated with the life cycle of an individual, as shown in Figure 5. Customers who recently entered into a loan agreement have a high LTV ratio. As young people dominate the group of new mortgagers, it follows that younger people are more indebted, which aligns with the life cycle hypothesis. Older people naturally have a lower LTV ratio, as they have typically amortized their loans over several years (Statistics Norway, 2023d). This pattern implies that younger individuals respond more strongly to interest rate changes. Furthermore, the fact that the average LTV ratio has increased drastically in the last decade further amplifies this effect, as discussed in Section 2.1.

To evaluate the robustness of individuals while controlling for life-cycle heterogeneity between age groups, we used a measurement of the LTV level compared with the individual's age group. We assigned those between the 80th and 98th percentiles of the LTV level for their age group as the treated group. They are relatively more exposed to interest rate changes. We labeled those in the 2nd to 20th percentiles as the control group because they are relatively unexposed to interest rate changes. This approach implied that the control group was also treated to a certain extent. However, the treatment difference was significant because the exposed group was, on average, more than twice as indebted (Table 2). The selection left us with 850 treated individuals and 730 untreated individuals for the interest rate cut period, and 962 treated individuals and 1103 untreated individuals for the hike period. The LTV and age distributions of the financially robust and financially exposed groups are shown in Figure 8. Using the age-adjusted measure greatly balanced age distributions, although they did not perfectly match. Because we used quantiles to construct financially exposed and robust data, it was natural that the LTV distributions overlapped slightly around an LTV of 0.5. If an older person had an LTV of 0.5, they were much more likely to be exposed than younger people with an LTV of 0.5. As the treatment classification is based on age groups, the level of LTV among financially exposed and robust individuals was different at different age groups. This factor creates a highly uneven LTV distribution, as shown in Figure 8.

We omitted all individuals between the 20th and 80th percentiles of relative LTV and those below the 2nd and above the 98th percentile. By doing this, we isolated the exposed and robust individuals. Omitting those between the 20th and 80th percentiles ensured that the difference between the two groups was significant enough to ensure a sizable difference in the treatment magnitude between the treatment and control groups. Outliers were omitted by excluding the far ends of the LTV distribution.

Another reason for using an LTV measure relative to age as a proxy for financial robustness is that age and fear of COVID-19 are correlated. Recurring surveys from The Norwegian Directorate of Health (2022) during the pandemic showed that the fear of becoming infected was generally strongly correlated with age. Because this likely caused different age groups to curb consumption differently, we avoided this issue by age-adjusting our treatment measures.

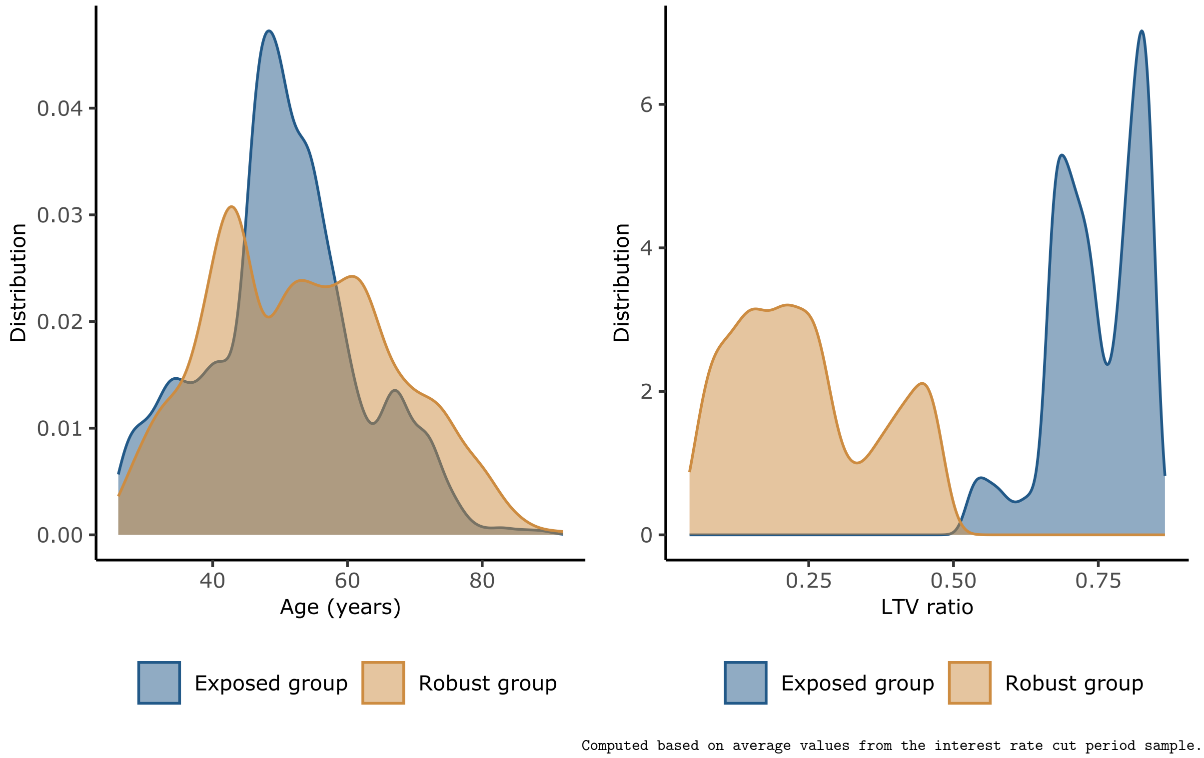


Figure 7: Age and Loan-to-Value Ratio Distribution

5.3 Timing of Treatment

We carefully set the periods of our analyses to when the policy rate changes were transferred to mortgagors' loan interest rates. We consider the actual change in the mortgage loan interest rate as the treatment time. This is important, as we do not aim to estimate anticipation effects, but rather the effect of actual changes in disposable income. We considered a period of 3-4 months before and after treatment to allow the consumption response to materialize and to have a reasonable comparison period.

The first period we analyzed, the interest-rate-cut period, was from December 2019 to May 2020. After the initial shock of the COVID-19 pandemic in March 2020, the Norges Bank decided to lower its policy rate by 125 basis points over the course of one week in March 2020. Typically, there is a lag of six weeks from policy rate changes to banks adjusting their loan interest rates to consumers. However, there was a deviation from this practice owing to the special situation surrounding the COVID-19 pandemic. The interest rate cut somewhat benefited all mortgagers simultaneously. Specifically, for our sample, as seen in Figure 4, the March cuts in the policy rate were partly passed on to mortgagers' loan interest rates immediately, while the remainder was transferred in June. To capture the effect of one interest rate shock, we define the post-treatment period as March-May 2020. The pre-treatment (comparison) period was defined as the period from the beginning of December 2019 to the end of February 2020. To avoid capturing the subsequent loan interest rate cut in June, we consider only the period up to May. By choosing such a short period, we aimed to evaluate the immediate short-term consumption response rather than the medium/long-term effect. Figure 9 shows that the treatment groups have fairly parallel trends.

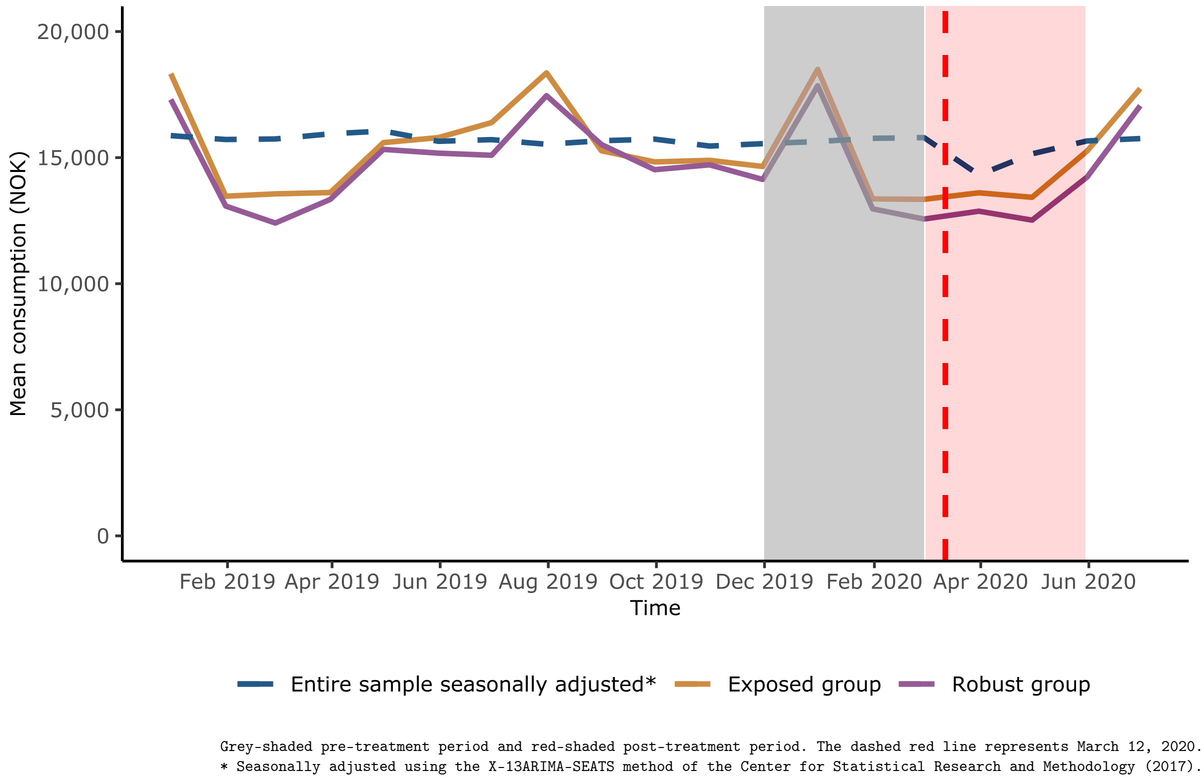


Figure 8: Consumption Trends - Cut Period

The interest rate hike period is from September 2021 to March 2022. We evaluated the period when the first interest rate hikes were transferred to the sample. The first policy rate hike came from the Norges Bank in September 2021, and was passed on to mortgagers' loan interest rates in December and January (Figure 4). Using the same arguments as for the interest rate-cut period, we seek to avoid estimating the effect of the subsequent series of interest rate increases. Consequently, treatment was initiated in December 2021 and continued until March 2022. Observing the individuals for a couple of months after the full treatment indicated that the interest rate changes had time to materialize in consumption.

Grey-shaded pre-treatment period and red-shaded post-treatment period.
* Seasonally adjusted using the X-13ARIMA-SEATS method of the Center for Statistical Research and Methodology (2017).

Figure 9: Consumption Trends - Hike Period

5.4 Heterogeneity Between Control and Treatment Group

In addition to a high LTV, individuals in the exposed group differed from those in the robust group in other characteristics. The heterogeneity is shown in Table 2. In general, the exposed individuals possess fewer liquid funds and larger loans. There were also higher shares of males and private sector workers in this group. Furthermore, there is a lower proportion of residents in large urban areas. This is problematic for the first part of our analysis in which COVID-19 restrictions play a significant role in individuals' ability to consume. However, the age distribution between the treatment and control groups was relatively homogenous, indicating that we circumvented the problem of a high correlation between age and LTV.

The fact that the exposed group has higher loans and possesses smaller liquid funds favors this analysis, as these traits strengthen the assumption that this group is less financially robust than the "robust" group. These results allowed us to confirm the label of these groups as financially exposed and robust. We do not demand that further criteria be considered part of the treatment group, as this would lead to fewer observations, and hence, a significant loss in degrees of freedom. Limiting the degrees of freedom decreases the precision of the analysis, which is a concern because of the relatively smaller size of our dataset compared with earlier studies. Another concern with basing the treatment on other financial variables such as deposits is that observations are possibly deficient and individuals' full balance sheets cannot be observed.

Table 2: Descriptive Statistics for Treatment Groups - Cut Period

	Exposed individuals (N=850)	Robust individuals (N=730)
Consumption (NOK)		
Mean (SD)	14,800 (± 7,500)	14,200 (± 7,200)
Median [Min / Max]	14,100 [0 / 39,200]	13,900 [0 / 39,200]
Deposits (NOK)		
Mean (SD)	89,200 (± 199,100)	232,200 (± 366,700)
Median [Min / Max]	28,700 [-100 / 2,857,200]	103,000 [100 / 4,075,500]
Loan interest rate		
Mean (SD)	3.05 (± 0.41)	2.75 (± 0.3)
Median [Min / Max]	3 [1.53 / 4.9]	2.72 [1.48 / 3.9]
LTV ratio		
Mean (SD)	0.74 (± 0.08)	0.25 (± 0.12)
Median [Min / Max]	0.75 [0.25 / 0.86]	0.23 [0.04 / 0.48]
Loan size (EAD)		
Mean (SD)	3,036,800 (± 1,487,900)	1,385,600 (± 1,126,900)
Median [Min / Max]	2,678,900 [264,500 / 9,976,500]	1,012,000 [29,600 / 7,523,600]
Large buffer (1 = yes)		
Mean (SD)	0.16 (± 0.36)	0.37 (± 0.48)
Median [Min / Max]	0 [0 / 1]	0 [0 / 1]
Debt expander (1 = yes)		
Mean (SD)	0.08 (± 0.27)	0.05 (± 0.21)
Median [Min / Max]	0 [0 / 1]	0 [0 / 1]
Occupation		
Private sector	603 (71 %)	342 (47 %)
Public sector	121 (14 %)	144 (20 %)
Retired	77 (9 %)	129 (18 %)
Self-employed	21 (2 %)	20 (3 %)
Missing	28 (3.3%)	95 (13.0%)
Co-dependent (1 = yes)		
Mean (SD)	0.58 (± 0.49)	0.52 (± 0.5)
Median [Min / Max]	1 [0 / 1]	1 [0 / 1]
Age (years)		
Mean (SD)	50.04 (± 11.46)	52.74 (± 13.62)
Median [Min / Max]	50 [26 / 88]	52 [26 / 92]
Gender		
Female	281 (33 %)	320 (44 %)
Male	569 (67 %)	410 (56 %)
Large Urban Area (1 = yes)		
Mean (SD)	0.68 (± 0.47)	0.8 (± 0.4)
Median [Min / Max]	1 [0 / 1]	1 [0 / 1]

Note:
See the appendix for a full description of the variables. Based on the period December 31, 2019, until May 2015, 2020.
Continuous values greater than 1,000 are rounded to the nearest hundred, while values that are less are rounded to the nearest two decimal places.

5.5 Model

Our main model is presented in Equation 5:

$$\log(Consumption)_{it} = \beta_0 + \beta_1 post_{it} + \beta_2 Exposed_{it} + \beta_3 Post_{it} * Exposed_{it} + \boldsymbol{X}'\delta + \varepsilon_{it} \quad (5)$$

Where subscript i represents the robust and exposed groups, respectively. The subscript *post* indicates whether the variable indicates the *post* interest change period. The model is equivalent for both interest-rate hike and cut periods. The β_0 captures the constant term, which is the y-intercept. β_1 indicates the baseline percentage difference between the exposed and robust groups in the pre-treatment period. β_2 indicates the percentage difference in consumption between the pre- and post-periods for the control group.

The β_3 coefficient represents the DiD estimate as the interaction term between the exposed group and the post-treatment period. If the coefficient is significant, then there is a significant difference in consumption development between the robust and exposed groups in the pre- and post-period.

The model includes a set of covariates captured by the $\boldsymbol{X}'$ vector, where the δ vector is the coefficient vector for controls. For some covariates, an interaction with the post-treatment period was included to capture heterogeneous responses to the surrounding macroeconomic environment. In Section 6, we present several different versions of Equation 5, in which the $\boldsymbol{X}'$ vector contains different sets of covariates to analyze and control for different sets of covariates.

5.6 Model Specifications

We employed several tactics to control for heterogeneity between the control and treatment groups on characteristics suspected to be correlated with consumption, but not with financial exposure. By including control variables, we limited concerns about omitted variable bias. Therefore, we aim to isolate the interest rate effect. First, we ran the model with a set of observable covariates that we believed to be influential. Additionally, there is a concern regarding heterogeneous responses to the surrounding economic situation, which adds bias to the estimated effect. We limited this concern to the interaction controls.

All specifications used to estimate heterogeneity in the consumption response are based on Equation 1. We estimated four different model specifications that vary, in which the control variables are included in the $\boldsymbol{X}'$ vector.

Model 1 is the baseline DiD model without any additional explanatory variables. We estimated this model to capture the baseline differences between the exposed and robust groups. In Model 2, we added control variables for co-dependency, gender, and retirement. For the interest rate-cut period, we added a control variable for the unemployment level in the given month. A *co-dependent* covariate was added to control for any systematic differences in consumption levels between those solely responsible for their loans and those with a co-borrower. It was reasonable to assume that those who share household expenditure with a second person have different consumption patterns. For instance, one party may handle mortgage expenses, whereas the other may pay for other commodities. From our dataset, it was apparent that those who were codependent consumed less than those who were not. The co-dependency covariate controls for bias originating from the slightly greater sample size in the financially exposed group with a co-borrower. The *gender* control variable is introduced because of different consumption patterns between genders and because the exposed group has a larger share of men than the robust group. In addition, our data show that men consume slightly less than women do.

Additionally, we included a control for retirement, as we expected retirees to have a different consumption pattern than the rest of the population. This is partly due to the lack of holiday pay and the fact that they may respond differently to macroeconomic shocks. During the COVID-19 pandemic, it was even more likely that consumption patterns would have differed, because older people were particularly vulnerable to infection. Heterogeneity in fear levels and risk perception likely affected consumption responses. In addition, our data set shows that retirees consumed less than the rest of the sample. As the share of retirees in the robust group was twice that of the exposed group, it was necessary to be controlled (see Table 2). The control for the unemployment level was introduced only in the interest rate-cut period because unemployment varied severely during the rate-cut period due to the first lockdown, when many people lost their jobs. Unemployment did not vary significantly during the interest rate-hike period. Hence, we did not consider the unemployment level during this period.

In Model 3, we included three additional control variables: *Large Buffer, Debt Expander,* and *Large Urban Area*. The control for *Large Buffer* is added in line with the findings of Fagereng et al. (2021), who find heterogeneity in MPCs from transitory income shocks at the high and low ends of the liquid wealth distribution. We hypothesized that those holding large buffers are more robust to interest rate changes and have a greater ability to smooth consumption during interest rate shocks. This is in line with buffer-stock theory (Carroll, 1997) and implies that those who hold large buffers maintain a more constant level of consumption.

Furthermore, we included the control variable *Debt Expander,* to identify those who take up new debt during the period. Because of interest rate cuts, credit becomes more accessible. Customers can further increase their loans when interest rates are reduced. Our dataset showed that during an interest rate hike, the individuals who increased debt were approximately equal between the robust and exposed groups. Conversely, during the interest rate-cut period, we observed a higher share of debt expansion in the exposed group than in the robust group. Due to the nature of the financially robust group, there was a meager share that was credit-constrained. Hence, they could borrow whenever they wanted. In the financially exposed group, it was reasonable to assume that there was a significant share of credit-constrained individuals owing to Norwegian lending regulations (Finansdepartementet, 2022). This pattern meant that a larger share of the exposed group experiences went from being credit constrained to having access to increased credit. Some people are likely to take advantage of this. Hence, they are likely to increase their consumption in subsequent months owing to liquidity replenishment. The Debt Expander dummy variable captures this effect.

We also included a control variable to account for those residing in large urban areas. We did this because of the observed heterogeneity between the control and treatment groups in the proportion of people living in large urban areas. The consumption patterns of these individuals may also differ from those of individuals living outside large urban areas. Any differences may have been amplified because infection control measures were more restrictive in urban areas than in rural areas during the COVID-19 pandemic. This is a factor relevant to both the interest rate cut and hike periods, as there was a lockdown in at least some parts of Norway at some point during both periods.

In Model 4, which is our main model for both the interest rate cut and hike periods, we added several interaction terms between several of the covariates in the previous models and the *post-treatment* period. By doing this, we mitigated the concern that these variables are subject to different trends during the analysis periods for reasons other than interest rate changes. We introduce an interaction between *Large Buffer* and *Post* to control for the possibility that these individuals smooth their consumption to a larger degree than those who hold small buffers during interest rate changes. Furthermore, we introduced an interaction between *Debt Expander* and *Post* to control for trend differences between those who increased their debt during the period. We also introduced an interaction between *Large Urban Area* and *Post*, as there were differences in the restrictive measures between urban and rural areas. As mentioned, there is some heterogeneity between the robust and exposed groups regarding the share of people living in large urban areas, making this an important control variable.

6 Results

This section presents the results of the model specifications. The results for the interest rate cuts and hike periods are presented separately. As we log-transformed the dependent variable, we interpreted the coefficients as percentage changes. As the independent variables are dummy variables, except for the unemployment level, we did not log transform them.

6.1 The Interest-Rate Cut Period

Table 3 reports the estimates from our analysis of the interest-rate cut period.

Our baseline model, Model 1, suggests no initial difference in consumption between the groups during the pre-treatment period. We estimate the overall decrease in consumption in the post-treatment period, denoted by the *Post* coefficient. This decline was natural due to the COVID-19 pandemic and its restrictions on consumption. In Model (1), the DiD coefficient *Post*Exposed,* given by the β_3 coefficient in Equation 5 is estimated as 0.082. This result is significant at the 10% confidence level. This indicates that the financially exposed group cuts its consumption less than the robust group when faced with an interest rate cut at the beginning of the pandemic.

In Model 2, we added control variables for sex, codependency, unemployment level, and retirement. The DiD coefficient, β_3, remains robust to these controls and is significant at the 10% confidence level with a point estimate of 0.082.

In Model 3, the DiD coefficient, β_3, is 0.081 and is significant at the 10% level. This estimate is almost identical to that of Model 2. In Model 3, we included three additional dummy variables to control for other characteristics, as mentioned in section 5.6. We also included a control for those holding a *Large Buffer*, which indicated no significant difference between their consumption and that of those who did not hold a *Large Buffer*. We included a control for debt expanders and found that these individuals consumed 24.2% more than the rest of the sample. This difference is statistically significant at the 1% level. We also added a control variable for those living in large urban areas. We found that these individuals consumed 4.6% less than those who did not live in large urban areas. This difference was statistically significant at the 5% level.

In Model 4, our main model, we introduced several interaction terms that controlled for the expected differences in adaptation to the COVID-19 pandemic. The result of the DiD coefficient, β_3, is robust to include these control interactions and is significant at the 10% level, with a point estimate of 0.076. The point estimate of the *Debt Expander* control included in Model 4 is reduced in magnitude compared with Model 3 when the interaction term is included and is no longer significant. This reduction was likely because part of the effect occurred during the treatment period, thereby reducing the pre-period estimate. Regarding the *Large Urban Area* variable, we observed a magnified negative effect, likely because of the different trends between central areas and other areas during the pandemic. However, this period-specific trend was insignificant, as evidenced by the interaction between *Post* and *Large Urban Area*.

Table 3: Regression Results - Cut Period

	Dependent variable:			
	Log(Consumption)			
	(1)	(2)	(3)	(4)
Exposed	-0.016	-0.015	-0.035	-0.032
	(0.030)	(0.029)	(0.030)	(0.030)
Post period	-0.148***	-0.175***	-0.175***	-0.242***
	(0.030)	(0.033)	(0.033)	(0.053)
*Exposed * Post period*	0.082*	0.082*	0.081*	0.076*
	(0.043)	(0.043)	(0.043)	(0.044)
Large Buffer			-0.045	-0.056
			(0.028)	(0.039)
Debt Expander			0.242***	0.175***
			(0.042)	(0.063)
Large Urban Area			-0.041*	-0.056*
			(0.022)	(0.030)
*Post * Large Buffer*				0.022
				(0.056)
*Post * Debt Expander*				0.131
				(0.083)
*Post * Large Urban Area*				0.028
				(0.044)
Unemployment level control	No	Yes	Yes	Yes
Co-dependency control	No	Yes	Yes	Yes
Gender control	No	Yes	Yes	Yes
Retirement control	No	Yes	Yes	Yes
Observations	8,495	8,495	8,495	8,495
R^2	0.003	0.010	0.015	0.015
Adjusted R^2	0.003	0.010	0.013	0.013
Residual Std. Error	0.987 (df = 8491)	0.984 (df = 8487)	0.982 (df = 8484)	0.982 (df = 8479)
F Statistic	9.606*** (df = 3; 8491)	12.685*** (df = 7; 8487)	12.485*** (df = 10; 8484)	8.683*** (df = 15; 8479)

Note:
*p<0.1; **p<0.05; ***p<0.01
Pre-treatment period from December 1, 2019, to February 29, 2020.
Post-treatment period from March 1, 2020, to May 31, 2020.

6.2 The Interest Rate Hike Period

Table 4 presents our main findings from the analysis of the interest rate-hike period. The models are specified similarly to the interest rate cut period, except that we do not include a control for the unemployment rate, as explained in Section 5.6.

Model 1 shows a baseline difference of 5.1% between consumption of the exposed and robust groups, significant at the 10% level, as indicated by the *Exposed,* β_1 coefficient in Model 1. No significant difference exists in the control group's consumption between the pre- and post-periods, as indicated by the non-significant *Post* variable, β_2. The non-significance of the DiD coefficient, β_3, *Exposed*Post* indicates no significant effect of the increased interest rate on the consumption development heterogeneity in the robust and exposed groups.

In Model 2, when adding the same controls as for the interest rate cut, the baseline difference in consumption between the exposed and robust group is no longer significant, as indicated by the *Exposed, β_2,* coefficient. The other results remained unchanged. There was still no significant effect of the DiD variable, β_3, *Exposed*post*.

In Model 3, we added the same control variables as those for the interest-rate cut period. We demonstrate that those holding *Large Buffers* consume 5.9% more than those not holding large buffers. This difference is statistically significant at the 1% level. *Debt Expanders* consume 16.2% more than those who do not expand their debt. This variable is significant at the 1% level.

In Model 4, we included several interactions to account for differences in consumption development during the treatment period. However, the DiD coefficient, β_3, *Post * Exposed*, was not significantly different from zero. We also added an interaction term between *Debt Expanders* and the post-treatment period. There was no significant difference in consumption levels between debt expanders and non-debt expanders during the pretreatment period. However, this effect was significant during the post-treatment period. It is also apparent that the difference in consumption between those with and without large buffers is not affected by interest rate shocks. This is a more general pattern because the interaction term *Post*Large Buffer* is insignificant, while *Large Buffer* remains significant at the 1% level, with a point estimate of 0.084.

Table 4: Regression Results - Hike Period

	Dependent variable:			
	Log(Consumption)			
	(1)	(2)	(3)	(4)
Exposed	0.051*	0.044	0.051*	0.054*
	(0.028)	(0.029)	(0.029)	(0.030)
Post period	-0.033	-0.033	-0.032	-0.069
	(0.025)	(0.025)	(0.025)	(0.049)
*Exposed * Post period*	0.004	0.003	0.002	-0.004
	(0.037)	(0.037)	(0.037)	(0.040)
Large Buffer			0.059***	0.084***
			(0.021)	(0.032)
Debt Expander			0.162***	0.074
			(0.033)	(0.055)
Large Urban Area			-0.009	-0.060**
			(0.020)	(0.030)
*Post * Large Buffer*				-0.044
				(0.042)
*Post * Debt Expander*				0.158**
				(0.069)
*Post * Large Urban Area*				0.090**
				(0.041)
Co-dependency control	No	Yes	Yes	Yes
Gender control	No	Yes	Yes	Yes
Retirement control	No	Yes	Yes	Yes
Observations	11,426	11,426	11,426	11,426
R^2	0.001	0.007	0.009	0.011
Adjusted R^2	0.001	0.007	0.009	0.009
Residual Std. Error	0.976 (df = 11422)	0.973 (df = 11419)	0.972 (df = 11416)	0.972 (df = 11411)
F Statistic	3.628** (df = 3; 11422)	13.458*** (df = 6; 11419)	11.922*** (df = 9; 11416)	8.741*** (df = 14; 11411)

Note:
*p<0.1; **p<0.05; ***p<0.01
Pre-treatment period from September 1, 2021, to November 30, 2021.
Post-treatment period from December 1, 2021, to March 31, 2022.

6.3 Main Findings

The main finding is that the interaction term between the exposed group and the post-treatment period is significant at the 10% significance level during the interest rate-cut period but not during the interest rate-hike period. The results indicate that in the short run, exposed individuals respond more aggressively to the interest rate cut early in the pandemic than robust individuals. We find no significant effects of the interaction between the exposed and post-treatment for the interest rate-hike regressions, indicating that the difference in consumption development between the two groups is unaffected by the interest rate hike.

The findings support the hypothesis of a short-term interest rate cash flow channel during the interest rate-cut period but not during the interest rate-hike period. We included several interaction terms to add controls for non-parallel trends between different subgroups. It is important to add controls for interactions during both the interest rate hike and interest rate-cut periods, as period-specific trends may correlate with the control variables, which may bias the estimates.

The determination coefficients of the models, R^2, remained very low throughout the analysis. Low explanatory power does not need to be an issue, and may only reflect that the confidence intervals of our models are very large, which is not unusual for macroeconomic analyses. Other factors, besides interest rate levels, affect consumption, which may make our model imprecise. Seasonal effects, which can be perceived as shifts in consumption over time, give the outcome variables considerable variability. Personal preferences amplify this variability.

7 Robustness checks

To limit several significant weaknesses of our dataset and increase the trustworthiness of our results, we performed several robustness tests that considered the main issues.

7.1 Parallel Trends

The parallel trend assumption is essential for DiD analysis. Given that the treatment and control groups would have experienced parallel consumption trends in the absence of an interest rate shock, we can attribute any difference in consumption development to heterogeneity in the interest rate shock. If the groups did not show parallel trends, the analysis would have been biased. Hence, it is crucial to verify the validity of this assumption. When analyzing consumption patterns and responses, this is even more critical because seasonal effects play an important role. Seasonal effects on consumption between months may outweigh the possible effects of interest rate changes. It is also important to consider that seasonality may differ between the two groups based on heterogeneity in characteristics. If the seasonality differs, the results may be biased. However, given the parallel seasonal trends, the seasonality of consumption does not bias the analysis. We investigated the parallel trends assumption by plotting the pre-trends of consumption 12 months before interest rate changes for both the treatment and control groups. By plotting a full year of observations before treatment, we efficiently captured any differences in seasonal patterns.

The consumption pre-trends are shown in Figures 9 and 10. The figures show the consumption patterns before both the interest rate hike and interest rate cut for the robust and exposed groups. Several interest rate changes in the years before COVID-19 can be interpreted as distinct treatment periods that may have heterogeneously affected the consumption of the groups. We observe that the parallel trend assumption is much stronger during the period before the interest rate increase, which lends credibility to this part of our analysis. This pattern also strengthens the assumption that interest rate changes in the period leading up to interest rate cuts make consumption trends between the two groups less parallel.

Having parallel trends before treatment does not necessarily mean that they would have continued in the absence of treatment; however, it provides a good indicator. We also observe that the original consumption levels were relatively similar, albeit slightly higher, for the exposed group during the pretreatment period of the interest rate hike. There was no significant difference in interest rate cuts between the two groups. This finding strengthens the assumption that the two groups were sufficiently similar for comparison. However, as mentioned earlier, the financially exposed and robust groups differ in other observable covariates, which may bias the comparison because these differences may be correlated with consumption decisions but not with financial robustness.

7.2 Propensity Score Matching

In Section 5.4, we discussed heterogeneity between the financially robust and financially exposed groups. The differences in the observed characteristics may be correlated with consumption decisions but not with financial robustness, which may bias our analysis estimates. We employed propensity score matching to control for the heterogeneity of the observed characteristics. Matching techniques allow us to alter datasets by choosing and weighing observations such that the groups become more balanced on the given parameters. Choosing covariates to base the matching and selecting the matching method is critical to this data-generating process. First, we used optimal pair matching, a matching technique implemented by Ho et al. (2011), using the MatchIt library in R by Ho et al. (2011). Optimal pair matching is a matching algorithm that creates a data subset that is more balanced than before the matching. This method matches the observation level and, using logistic regression, optimizes the distance criterion. This distance is optimized by choosing observations that share characteristics that make the observations more equal in terms of the likelihood of receiving treatment.

We base the matching on key variables that may be correlated with consumption decisions but not necessarily with financial robustness. Additionally, there was an imbalance in these variables between the two groups. Hence, they have the potential to bias these estimates. We used the variables *Gender*, *Private sector, Retired, Large Urban Area,* and *Co-dependent*. This imbalance can be seen in the descriptive statistics in Table 2 and Appendices 1, Table 6. When the datasets were matched, we observed an improvement in the balance of summary statistics of these variables. This was observed by comparing the balance for the full dataset in Table 17 with the matching outputs in Table 18[11]. The regression results for both the interest rate-cut and interest rate-hike periods were robust when using datasets matched using optimal pair matching, as seen in Tables 7 and 8.

We also tested the generalized full matching to determine whether the results were robust to an alternative matching algorithm (Ho et al., 2011). The generalized full matching technique is different from optimal pair matching. It is a powerful algorithm that matches a sample by splitting the observations into subclasses based on the likelihood of receiving treatment. It then weighs these subclasses differently to obtain control and treatment groups that are perfectly balanced on the matched covariates. A matching summary can be observed in the matching outputs in Appendix 4 and Table 19. It follows from the method that some observations will be weighted higher in the regression than others, which is both a strength and weakness of this technique (Greifer, 2023). It is apparent that the robust group is weighted lower than the exposed group when employing generalized full matching because the effective sample size (ESS) is significantly lower for the control group after matching, as can be seen from the sample size table (Table 20).

The main results are robust to generalized full matching. However, the most extensive model is not significant for the interest rate cut period, with a P-value of approximately 0.105, compared with approximately 0.085, which is the result of the main specification without matching. This approach does not change the main point of the results, namely, that the results involve a significant degree of uncertainty. The results for the interest rate-hike period are analogous to those for the unmatched dataset. We report the regression results based on the matched data using generalized full matching in Appendices 2, 9, and Table 10.

[11] Note that the matching summaries for both the optimal pair matching and the generalized full matching, presented in Table 18 and 19, are only for the interest rate cut period. The summaries for the interest rate hike period are analogous but left out of the article.

7.3 Two-way Fixed Effects

One concern with the simple two-group, two-period DiD estimation is that unobserved time- and group-invariant variables affect the heterogeneity in the short-term consumption responses between the two groups.

We address this by estimating a general two-way fixed effects (TWFE) DiD model, which includes monthly and group-level fixed effects. This prevents us from including controls for observable characteristics that are time-invariant within the exposed and robust groups, as in the main model. However, this estimation technique enables us to control for time- and group-invariant variables by adding group and month fixed effects to the model. We estimate this model using Equation (6):

$$\log(Consumption)_{it} = \alpha DiD_{it} + \phi_i + \psi_t + \mu_{it} \tag{6}$$

In equation 6, the subscript i is a group indicator and the subscript t is a time indicator. α $\phi$is the DiD coefficient, ϕ_i is the group-level fixed effects term, and ψ_t is the time fixed effects term. μ_{it} is an idiosyncratic error term.

The results of this specification for both the interest rate cut and hike are shown in Appendix Table 11. These results are consistent with our main results in that they are similar in both point and precision estimates during both the interest rate cut and hike periods.

7.4 Interaction Tests & Placebo Regressions

We employ interaction tests to further test for the possibility of other group-specific time trends during the analysis period that we have not accounted for. To mitigate this concern, we added two more interaction terms individually to the main specification to determine if the results are prone to the inclusion of these terms. By interacting the post period with *Gender* and *Co-dependency* in addition to the other interaction controls included in Model 4 in Tables 3 and 4, we add controls for two other possible heterogeneous trends after the interest rate changes. The results of these interaction tests are robust when additional interaction tests are included, as shown in Appendix 2, Tables 13 and 14.

When running the regression on other periods with no interest rate changes, we find no significant heterogeneity in the development of consumption between the exposed and robust groups. We examined two periods in which no interest rate changes occurred to avoid capturing interest rate effects. We set the first period to 2017 to compare our results with a placebo period in which there were no interest rate changes over an extended period. Additionally, the parallel trend assumption is tested during a different period with a different macroeconomic environment. The second period is from mid-2020 to mid-2021. We chose this period because it is close to the analysis period. Thus, this regression provides further insight into whether the parallel trend assumption is plausible (Figure 4). The results of these two sets of regressions show that when no treatment occurred, no significant differences in the heterogeneity of consumption development between the robust and exposed groups were estimated. The results of the placebo regression are presented in Table 12.

We also performed a second set of placebo regressions, in which we used different groups to assign treatment status. We performed a robustness check to select the treatment groups based on different relative LTV. When choosing relative LTV levels close to the median rather than at the far end of the distribution, there should be no significant effect from the regression. We chose age-adjusted relative LTV quantiles between the 40^{th} and 50^{th} percentiles as the control group and the 50^{th} to 60^{th} percentiles as the treatment group. As expected, the results show no significant treatment effect either during the interest rate cut or the interest rate hike period. The results of this set of regressions can be seen in Tables 15 and 16.

7.5 Tests

We tested for heteroscedasticity in all models using the Breusch-Pagan test. We found that the p-value for the test was below the 5% significance level, suggesting that we should add a control for heteroscedasticity. Hence, we use heteroscedasticity-robust standard errors. Because we considered only two groups that were not sampled in other clusters, we did not cluster the standard errors.

Multicollinearity was a potential concern in this analysis. This was examined in the correlation coefficient matrix (Figure 11 and 12) using variance inflation factor (VIF) scores. We observed acceptable levels of correlation coefficients and multicollinearity. However, when we added multiple parameters that interacted with the *post* variable, we obtained high VIF scores. This is expected, because these type of interaction terms produce high VIF scores. However, this is not a concern because these interactions are merely controls and we do not have VIF issues in the level variables.

8 Discussion

Section 6 (Tables 3 and 4) presents our results, which indicate a heterogeneous short-term consumption response between the robust and exposed groups following an interest rate cut in March 2020. We found that financially exposed households with high LTV ratios increased their consumption more than financially robust households with low LTV ratios did. This is apparent because *Post*Exposed* in Model 4 in Table 3 is positive and significant. Conversely, we found no heterogeneity in consumption development between the groups after the loan interest rate increases in December 2021 and January 2022. This can be observed from the insignificant *Post*Exposed* coefficients in Model 4 of Table 4.

The positive result from the interest rate-cut period is consistent with the theoretical cash flow channel for interest rate changes. Previous studies have estimated a consistent significant cash flow channel. Conversely, the results contradict the cash flow channel during interest rate hikes. This is because the financially exposed group receives a greater decrease in disposable income when the interest rate increases compared to the financially robust group. However, we found no evidence that they reduced their consumption.

We must underline that these results are highly uncertain because of inaccurate data, small sample sizes, and considerable heterogeneity between groups as the primary causes.

Next, we highlight the key mechanisms that explain our results. Specifically, we emphasize the cash flow channel and individual heterogeneity in risk aversion, through which the substitution and precautionary savings channels work. We also discuss the possible effects of forward guidance. These aspects require further investigation to fully understand their implications.

8.1 The Cash Flow Channel: Overestimation

Our estimates of the heterogeneous consumption response of approximately 8% after the interest rate cut in March 2020 and 0% after the interest rate hike in the winter of 2021-22 cannot solely be attributed to the cash flow channel.

Given the summary statistics on customers' loan size, average interest rate, and remaining installments, we calculated the average DiD in monthly disposable income between the two groups to be approximately 353 NOK during the interest rate-cut period (Table 22). If both groups have an MPC of 1, which is a strong assumption, the difference mathematically corresponds to the computed DiD coefficient of equation 1 of 2.2% (Table 22). Our model produced results that were approximately 3-4 times the size of the computed effect. However, we could only document significance at the 10% level. This indicated that the estimated effect was associated with a large degree of uncertainty.

Analogously, we compute the average monthly effect during the interest rate hike to be -253 NOK, giving a computed DiD coefficient of approximately -1.5% for consumption between the two groups (Table 22). Our model estimates that the DiD coefficient is not significantly different from zero. The results indicate that in both the hike and cut periods, the exposed group, relative to the robust group, spends a larger proportion of its disposable income on consumption after the interest rate change.

Our findings for the cash flow channel during the interest rate cut are sign-consistent (share a positive sign) with several other studies, including Di Maggio et al. (2017) and Flodén et al. (2021). However, the magnitude of our findings differs from those of these studies. We found no significant cash flow effects during the interest rate hike period. Di Maggio et al. (2017) did not consider interest rate hikes, whereas Flodén et al. (2021) estimated interest rate shocks using a different method, in which the sign of the interest rate change is not important. Hence, our results contradict those of Flodén et al. (2021) for the interest rate hike period. Both studies primarily studied long-term effects, whereas we studied short-term effects, making them incomparable. Overall, our results are much stronger than the average findings in the literature during an interest rate cut, but weaker during an interest rate hike.

Interestingly, our model produces estimates larger than the computed effects for both the interest rate cut and hike periods. For both periods, the differences in characteristics between the financially exposed and robust groups likely meant that they reacted differently to their surroundings. As mentioned in section 7, we identify observable non-financial differences between the financially exposed and robust groups and balance the dataset using propensity score matching on these observable characteristics. The interest rate cut and hike results are robust to almost all the matching specifications, indicating that the underlying unobserved differences between the control and treatment groups affect their consumption decisions. Therefore, it is impossible to attribute the analysis results solely to the cash flow channels of interest rate changes. There are many plausible reasons why the cash flow channel fails to explain our results. They revolve around how heterogeneity between groups correlates with other behavioral aspects that also affect private consumption. This will be explained in detail in the following section.

One attenuating effect of the cash flow channel is voluntary deleveraging. As a result of the freeing up of funds due to an interest rate cut, U.S. data showed that some individuals chose to reduce their debt burden by voluntarily deleveraging their mortgages (Di Maggio et al., 2017). By taking advantage of their increased disposable income to make unscheduled repayments, individuals can improve their financial situation by reducing their monthly expenses. Di Maggio et al. (2017) found that those with high liquid asset levels were more likely to be deleveraged. They only had access to data for an interest rate cut and did not show whether this effect was symmetric for interest rate hikes and cuts. This reasoning suggests that the heterogeneous consumption response during an interest rate cut may be stronger if the robust group outnumbered the exposed group. However, few individuals deviated from their repayment schedules, suggesting that this effect was negligible.

8.2 Heterogeneity in Risk Perception

One may ask whether risk aversion influences how the two groups perceive their surroundings and make consumption decisions accordingly. Given that risk tolerance and financial exposure are correlated, this effect either strengthens or attenuates the effects of monetary policy on private consumption. However, this topic has not been researched extensively in macroeconomics.

The robust and exposed groups differ in their observable characteristics, which are the key to determining risk tolerance. Factors such as gender, income, and occupation are important for understanding risk perceptions (Sahm, 2012). The exposed group had a larger share of men and private sector workers, indicating that the exposed group had a higher level of risk tolerance.

Furthermore, the exposed individuals were more leveraged (Table 2), which may be partly explained by their higher risk tolerance. This finding is in line with Sahm (2012), who finds a positive relationship between indebtedness and risk tolerance. Our data show that indebtedness strongly correlates with age. Using the relative LTV quantiles by age category as our treatment group, we ensured that the difference in risk tolerance between the exposed and robust groups was not biased by the different age distributions in the two groups.

These factors indicate that it is likely that heterogeneity in risk perception between the two groups is an important channel contributing to the upward bias of the cash flow channel observed in the results in section 6. Next, we discuss the channels through which risk perception heterogeneity exists.

8.2.1 Substitution Effect

Heterogeneity in the groups' risk perceptions may have affected the differences in the substitution effect between the two groups (Yagihashi & Du, 2015). A simple two-period model of the consumption-saving decision, in accordance with Equation 1-4 in section 5.5, shows that an interest rate cut makes savings less attractive and encourages current spending. The opposite is true when interest rates increase. Individuals' risk perceptions may affect how they rush or defer their consumption, which is consistent with the substitution effect.

According to Yagihashi and Du (2015), the intertemporal elasticity of substitution is larger for the more risk-tolerant, as captured in the θ coefficient in Equation 3 and 4. Such results may partially explain large-point estimates during the interest rate-cut period. Given homogeneous inflation expectations, the exposed, more risk-tolerant group chooses to substitute more of its consumption to the present relative to the robust group. However, when faced with an interest rate increase, the substitution effect should, in isolation, lower consumption and increase savings among financially exposed individuals. Consistent with Yagihashi and Du (2015), this group has a higher level of intertemporal substitution.

Notably, the interest rate hike occurred simultaneously with the fear of higher inflation expectations. Duca et al. (2019) state that higher inflation expectations lead to lower real interest rates. According to the substitution channel, higher inflation expectations cause consumers to spend more today and lesser in the future (Duca et al., 2019). However, Reiche and Meyler (2022) show that this assumption of homogeneous inflation expectations is invalid. They argue that the traits we observe in the exposed group are associated with lower inflation expectations, which is intuitive, given their higher risk tolerance. Hence, the expected real interest rate of the exposed group may be lower than that of the robust group, attenuating the differences in their consumption responses to intertemporal substitution following interest rate changes. Thus, it is unclear what sign the inflation effect has on intertemporal substitution during an interest rate increase.

8.2.2 Precautionary Savings Effect

Concerns about job security effectively create uncertainty regarding future income. Significant economic uncertainty was particularly noticeable during the national lockdown in March 2020. Many people are at risk of losing their jobs, making their economic futures very uncertain. Individuals' precautionary savings closely relate to their levels of uncertainty. When uncertainty about one's future economic situation increases, precautionary savings increase to meet this uncertainty (Carroll and Samwick, 1997). Risk tolerance is negatively correlated with the perceived need for precautionary savings (Bommier & Grand, 2019; Kimball & Weil, 2009). In Section 3.4, we uncover the theory of risk aversion heterogeneity among people with different characteristics (Sahm, 2012). Based on her theories, it is reasonable to assume that the financially robust group is less risk tolerant than the financially exposed group. Hence, the financially robust group is likely to increase precautionary savings relative to the financially exposed group. Thus, they are likely to have a lower MPC owing to increased disposable income following an interest rate cut.

Fagereng et al. (2021) estimated the differences in MPC from lottery wins and found that the marginal propensity to save is higher for those in the highest quartile of deposits. This is consistent with the above discussion, in which we argue that financial robustness, consistent with the precautionary savings theory, is more likely to save a larger proportion of increased disposable income following positive income shocks.

Differences in precautionary savings may also affect differences in consumption responses during the interest rate hike period. There is a large degree of uncertainty during the interest rate increase. During this period, concerns about higher inflation began, as can be seen by comparing the last of Norges Bank's *Monetary Policy Report* from 2021 and the first from 2022 (Norges Bank, 2021c, 2022c). A U.S. study showed that those with high expectations for future inflation saved a larger proportion of the money they were granted in the CARE Act during the pandemic (Armantier et al., 2021). Assuming that the robust group is more concerned about future inflation, they are more likely to increase their precautionary savings and reduce their consumption than the exposed group. This may partially explain why we did not observe any differences in consumption responses during the interest rate-hike period.

In isolation, precautionary savings dampen the overall interest rate effect on consumption; however, due to heterogeneity in risk perception, the two groups save to different extents. This may explain the results of the present study.

8.3 The Expectation Channel: Forward Guidance

The forward guidance of the policy rate, which works through the expectation channel, can partly explain why we find only a heterogeneous consumption response during an interest rate cut. By comparing the two periods of interest rate changes, a hike was anticipated, whereas the cut was unexpected. The different nature of these two interest rate changes suggests that only an interest rate cut can be considered an unexpected shock. In early 2021, Norges Bank announced a policy rate hike through forward guidance (Norges Bank, 2021a). Central banks have adopted forward guidance over the past decade, in which they publish forecasts of future policy rates. Forward guidance provides economic agents with transparency and predictability, allowing them to adjust their future interest rates. However, the interest rate cut occurred unexpectedly, preventing people from having a chance to adjust their consumption in advance.

Given that individuals perceive the central bank's forward guidance and thus anticipate a change in expenses, they have the opportunity to adjust their consumption in advance. There may be heterogeneity in the adaptations to these new expectations because groups with different liquidity levels adapt differently. Druedahl et al. (2022) found that individuals holding the most liquid assets, namely robust assets, adjusted their consumption when notified about an upcoming interest rate reset, but not after the actual interest rate reset occurred. This is because they have the opportunity to adapt before the actual cash flow channel occurs owing to their liquidity levels. Analogously, they find that individuals with low levels of liquidity do not adjust their consumption when notified about the future reset but adjust after the actual interest rate reset has taken place. This is because they cannot adjust their consumption beforehand.

Translated into our setting, this means that the robust group was more likely to have taken forward guidance than the exposed group. Therefore, the robust group was more likely to have adjusted its consumption before the interest rate increase, which may have contributed to the insignificant differences in consumption responses during this period. Druedahl et al. (2022) primarily examined interest rate cuts, meaning that it is not generalizable for interest rate hikes.

These factors suggest that people adjust their consumption based on their expectations of future interest expenses. Moreover, through forward guidance, the central bank forecasted additional interest rate hikes, which affected expectations of future economic conditions.

8.4 Strengths and Weaknesses

8.4.1 Strengths

Our research design has several desirable features. Microdata from banks have not been widely examined in this research area. Bank data have the primary advantage of providing greater temporal resolution than is typical in previous research. Access to monthly bank data allows us to examine short-term effects, in contrast to the long-term effects typically captured by yearly register data. Few studies have been conducted on the short-term effects of monetary policy, which are critical for fully understanding its effects. Our study ventures into relatively unexplored areas and is a new contribution to both methods and datasets.

The empirical DiD approach, in which we assign treatment to those who are financially exposed relative to their age group, is a way to mitigate the concerns of a strong correlation with the life cycle of individuals. Treatment assignment is a strength of our research design, as it allows us to circumvent the inevitable correlation between age and financial exposure in terms of LTV and DTI. Another strength is the choice of the analysis period and short time span. By considering pre-treatment periods with no interest-rate changes and post-treatment periods with only one interest-rate change, we aim to isolate the sole changes. Hence, under the assumption of parallel trends in the periods leading up to interest-rate changes, any measured differences after the interest-rate reset are due to heterogeneity in their adaptation to interest-rate changes. This is one of the strengths of the proposed method.

The COVID-19 pandemic caused an abrupt shock to the economy, and Norges Bank lowered its interest rate at an unprecedented speed and magnitude. This shock is of great interest in the analysis. The cuts were sharp, sudden, and unexpected, indicating that consumers could not adjust their consumption in advance. Access to an unexpected interest rate shock of such a magnitude is rare and valuable for research purposes.

8.4.2 Limitations

Our study had several limitations as well. In this section, we discuss these issues in further detail and comment on their implications.

The strengths of this study include some of its foremost weaknesses. The dataset we employed limited our analysis because we did not have access to certain key variables that would have aided the analysis. We do not have a complete overview of individual balance sheets. As mentioned in several sections, this prevents us from observing the deposits, spending, and stock or bond holdings of other banks. We partially overcome these issues by filtering inactive customers from the panel. However, in line with a survey by Forbrukerrådet (2023), a significant proportion of individuals in the dataset likely have banking relationships outside BN Bank, which limited our research in several ways. First, we could not necessarily assume that the observed levels of deposits and spending reflect a representative sample. Second, we did not have reliable measurements of individual income, which has several implications. Combined with the fact that we did not have complete information on individuals' other banking relationships, we could not compute a measure of savings, which would have been valuable for the analysis.

Because of the lack of income data, we were forced to construct a measure of individuals' robustness without considering their income. Had we had access to income and savings data, we would have been able to produce a more detailed analysis with better financial robustness and a more reliable consumption measurement. In the Norwegian context, the only way of getting access to this type of "perfect" data is to get access to administrative register data. However, administrative data do not allow us to study short-term effects due to coarse temporal resolution. This type of data lends itself more towards the use of a methodology, as in Flodén et al. (2021) and Gerdrup and Torstensen (2018), who have a stronger focus on the full cash flow effect of interest rate shocks than on short-term heterogeneous effects.

Another concern is the representativeness of the population sample. For instance, we know from the population pyramid that our sample is overrepresented in southeastern Norway (Figure 7) and among men, especially in the age range of 40-60 years (Figure 6). This skewness could potentially bias our results and create challenges in providing external validity. This problem can be resolved by creating a sample that matches the population by using certain key parameters. However, considering the short time span present, doing so for our sample would severely restrict our degrees of freedom.

Differences in the observed characteristics between the control and treatment groups are another concern. A correlation between the LTV ratio, loan size, and deposit size is inevitable because these measures largely depend on each other. The correlation is not necessarily a weakness of the article since they all point in the same direction: The treatment group is more financially exposed, and the control group is more robust. More concerning are the differences in sector allocation, co-dependency, urban areas, and gender between the exposed and robust groups. These differences are concerning because we suspect that they correlate with financial behavior, but not debt levels. The effects we estimated were more due to these differences than to financial robustness. We added a control for this concern by including control variables and interaction terms, but our study would be more robust given the homogeneous treatment and control group. Another concern is that unobserved characteristics correlate with financial vulnerability, weakening the assumption that the groups are comparable. We addressed this issue by matching propensity scores and conducting a TWFE DiD analysis on the data.

Another limitation of our study is the size of the dataset. Given that a change in interest expenses can change consumption only slightly, we depend on a large sample to obtain precise estimates. Factors such as income, wealth, and seasonality affect consumption far more than interest rates, which explains the low explanatory power of our model (R^2). Our study included only approximately 2,000 individuals. Other studies that examine cash flow effects from interest rate shocks, such as Druedahl et al. (2022), Flodén et al. (2021), and Gerdrup and Torstensen (2018), use datasets with hundreds of thousands of observations. Another challenge with a smaller dataset is that it limits our ability to analyze various subsamples owing to the loss of degrees of freedom.

Another limiting factor was that some individuals in our control group may not have been as robust as expected. They might have a low LTV ratio relative to their age group because the bank may consider them ineligible for increased loans. This may be due to unemployment, payment defaults, or credit history. This might limit their access to credit, making them unable to take advantage of the decreased interest rate to increase their borrowing even if they have incentives to do so.

The endogeneity of the interest rates imposes some challenges on the analysis. The policy rate is not determined solely by exogenous factors, as central banks react to changes in economic conditions. The most notable are identification problems in which causal relationships are identified. There is a two-way causality between the policy rate and consumption level. The policy rate reacts to and affects macroeconomic conditions that also affect consumption simultaneously (Gulbrandsen, 2023). The fact that both the policy rate and consumption also react to other factors, including the unemployment level and inflation, makes it challenging to establish clear causal relationships.

The context of our study, conducted during the COVID-19 pandemic, further complicates our analysis. Preventive measures restrict individuals' ability to maintain spending on certain types of goods, disproportionately affecting the consumption of services over goods (see Figure 3). If the two groups initially had different consumption compositions of goods and services, this might cause bias in our estimates. Generalized full-matching partially mitigates these concerns.

Moreover, we encounter issues with self-selection, as loans are not randomly assigned to individuals, meaning that individuals in the treatment and control groups choose to take out the loans. It is unlikely that this choice was random and did not correlate with the underlying differences between the two groups. Individuals' willingness to take on larger loans and their associated exposures are likely to be correlated with their risk tolerance.

Given our dataset, which consists only of mortgagers and uses interest-rate resets as treatment timing, we partly violate the assumption that the control group remains untreated throughout the period because this group also faces an interest rate change. The control group receives treatment to a lesser extent than the treatment group, indicating a sizeable treatment effect. However, because we used the age-adjusted relative LTV as an indicator of receiving treatment, the size of the interest rate effect is not as large as it would have been had we used absolute financial exposure measures. However, this would have led to biased estimates due to age effects. Flodén et al. (2021) compared indebted households with debt-free households, and effectively had one group affected only by interest revenue and not interest expenses. We also included a control group that was treated to a certain extent. This can be justified by the fact that the alternative group of those without mortgages may not be comparable. In Norway, such households stand out as homeowners are predominant, as shown in Figure 2. Thus, those who do not own homes may not be comparable with those who do. Another alternative comparison group is those with FRMs who are unaffected by an interest rate change in the short-term but are still homeowners. However, this approach is not viable, because the share of FRM holders in Norway is extremely low (Statistics Norway, 2023e).

8.5 Implications and Further Research

The fact that the short-term effects of monetary policy have been studied to a limited extent is one of the main reasons this article is of interest. We point out a possible option for conducting research in this interesting and relatively unexplored part of the literature using administrative bank data.

In accordance with Norges Bank's targets, as described in Section 3.1, it is important to understand the consequences of monetary policy. This also includes a solid understanding of the short-term (1-3 months) effects. Insights into the sluggishness of short-term adaptation to interest rate changes are valuable. Monetary policy overreaction refers to central banks making several interest adjustments. Such an overreaction may occur if the central bank does not fully understand the consequences of the previous interest rate change before making the next change. Further research on how the economy responds in the first 1-3 months following interest rate changes may impact monetary policy. Our study indicates that the effects are asymmetrical for individuals with different levels of financial vulnerability. We highlight the need for further research on this subject and promote the increased use of banking data to understand different household responses to changes in the policy rate.

As the financially exposed group in our sample is more leveraged, it poses a greater risk of financial stability. Regarding Norges Bank's target to mitigate financial imbalances, the central bank is particularly interested in curbing the consumption of such groups. Through the cash flow channel, the exposed group is naturally struck harder by an interest rate change, as their interest expenses account for a larger share of their expenditure. Thus, the interest rate ought to work effectively through consumption by the exposed individuals. As we do not find significant results during the interest rate hike period, we find no evidence that such a pattern exists in the short term. Furthermore, the results of this analysis may improve the risk models for commercial banks. Bank exposure is directed toward mortgages secured by residential real estate. To withstand economic downturns, it is valuable for banks to gain insight into mortgagers' consumption patterns and how changes in interest rates affect their ability to provide service loans.

Our findings suggest that, over time, there will be an increased discrepancy in financial robustness between financially robust and exposed individuals. The results indicate that the exposed group increases its income relative to the robust group when faced with interest rate cuts, as suggested by the cash flow effect. The results also show that the exposed group does not symmetrically reduce its consumption when faced with an interest rate increase. Given that these effects remain in the long run, the discrepancy in financial robustness between the exposed and robust groups for each interest cycle will only accelerate. This feature is undesirable, because central banks focus on promoting financial stability. This finding may have implications for how central banks consider heterogeneous risk aversion when adjusting for monetary policy.

As mentioned in the previous section, our main concerns were related to data. One may resolve some of this study's shortcomings by accessing data from larger banks. A larger dataset would allow the selection of more comparable treatment groups and achieve more precise estimates. One approach could be to send surveys to a representative sample of banking customers to obtain data on other important characteristics that are unobserved by banks. Survey data were paired at the individual level with administrative bank data. One could also ask if they have other banking relationships; if they are codependent, one could cluster households together. Alternatively, pairing administrative register data with bank data, as in Druedahl et al. (2022), could solve many of the issues we dealt with. Such a data foundation would enable us to estimate the short-term effects more precisely and confidently. Several other minor steps could improve the study, such as clustering at the household level and obtaining better granularity of consumption measures.

In this study, we did not analyze whether the disposable income shock individuals considered when faced with interest changes is solely the amount of their installment changes, or if they instead considered the changed interest expenses. It seems natural for individuals to consider the installment amount, but they may also consider only interest expenses and view the reductions in their debt as savings. Hence, a decrease in interest expenses may be considered cash flow. It is beyond the scope of our study to consider this and is left to future researchers.

9 Conclusion

This study analyzes the short-term heterogeneity between how financially robust and exposed groups change their consumption when faced with interest-rate changes. This topic has received relatively little attention in the existing literature. We hypothesize that the exposed group will have a stronger consumption response to interest changes than the robust group, which is consistent with the cash flow effect. The cash flow effect theorizes that there will be a consumption response to interest rate changes through changes in disposable income, in addition to other interest effects, such as intertemporal substitution.

We analyzed both interest rate cuts and hikes to study whether any differences in consumption responses between the two groups are symmetrical when disposable income increases and decreases. We found that financially exposed consumers increase their short-term consumption compared with the financially robust group when they faced an interest rate cut in March 2020, although the significance was weak. This is consistent with the cash flow channel and the literature. Interestingly, we found that during the subsequent interest rate hike in the fall and winter of 2021-22, the financially exposed group did not differ in its short-term consumption trend from the financially robust group. This result contradicts the existing literature on long-term cash flow channels.

There is insufficient empirical evidence to attribute these results solely to cash flow channels. Instead, we point to several channels that may affect consumption heterogeneity. We highlight risk aversion heterogeneity, which particularly affects expectations through forward guidance and substitution channels. These channels are plausible contributors to overestimating short-term cash flows.

Our results remain significant or almost so, depending on the specification, even after employing severe matching techniques and TWFE DiD to implement control for this heterogeneity. This finding indicates that other unobserved time-variant effects influence the perception of interest rate changes heterogeneously among the two groups. Investigating these effects is a topic for future research.

This study crucially highlights the need for further research. The most important issue to resolve in our study was gathering better data to allow for a more precise and elaborate analysis. Further research is required to gain an improved understanding of the immediate effects of monetary policy. This may help central banks not overreact in their monetary policy decisions, and lead to a better understanding of how quickly a monetary policy passes through the economy. Our results also highlight the need for research on how risk aversion affects monetary policy pass-throughs at the individual level. If the most financially exposed individuals are also the most risk-tolerant, this may have implications for financial stability.

Ultimately, this study provides insight into how financial exposure affects short-term consumption responses when faced with interest rate changes. Despite the limitations of this study, the results shed light on short-term mechanisms and how risk aversion is likely to play a significant role in short-term adaptation.

References

Ando, A., & Modigliani, F. (1963). The "Life Cycle" Hypothesis of Saving: Aggregate Implications and Tests. *The American Economic Review*, *53*(1), 55-84. https://www.jstor.org/stable/pdf/1817129.pdf

Armantier, O., Koşar, G., Pomerantz, R., Skandalis, D., Smith, K., Topa, G., & Van der Klaauw, W. (2021). How economic crises affect inflation beliefs: Evidence from the Covid-19 pandemic. *Journal of Economic Behavior & Organization*, *189*, 443-469.

Black, S., & Cusbert, T. (2010). Durable Goods and the Business Cycle. *Reserve Bank of Australia,*(Bulletin). https://www.rba.gov.au/publications/bulletin/2010/sep/2.html

BN Bank ASA. (2023). *Presentasjon 4. kvartal 2022*. https://www.bnbank.no/globalassets/02_om-oss/finansiell-informasjon/rapporter/2022/4.-kvartal/presentasjon-q4-2022.pdf

Bommier, A., & Grand, F. L. (2019). Risk aversion and precautionary savings in dynamic settings. *Management Science*, *65*(3), 1386-1397.

Bonin, H., Dohmen, T., Falk, A., Huffman, D., & Sunde, U. (2007). Cross-sectional earnings risk and occupational sorting: The role of risk attitudes. *Labour Economics*, *14*(6), 926-937. https://doi.org/10.1016/j.labeco.2007.06.007

Brasch, T. v., Cappelen, Å., Holden, S., Lindstrøm, E. L., & Skretting, J. (2022). *COVID-19, tapt verdiskaping og finanspolitikkens rolle | Utredning for Koronakommisjonen*. Statistics Norway. https://www.ssb.no/nasjonalregnskap-og-konjunkturer/konjunkturer/artikler/covid-19-tapt-verdiskaping-og-finanspolitikkens-rolle%20-2022

Brubakk, L., & Sveen, T. (2009). NEMO-a new macro model for forecasting and monetary policy analysis. *Economic Bulletin (Norges Bank)*, *80*(1).

Carroll, C. D. (1997). Buffer-Stock Saving and the Life Cycle/Permanent Income Hypothesis. *The Quarterly Journal of Economics*, *112*(1), 1-55. https://doi.org/10.1162/003355397555109

Carroll, C. D., & Samwick, A. A. (1997). The nature of precautionary wealth. *Journal of Monetary Economics*, *40*(1), 41-71. https://doi.org/10.1016/S0304-3932(97)00036-6

Center for Statistical Research and Methodology. (2017). *X-13ARIMA-SEATS Reference Manual*. https://www2.census.gov/software/x-13arima-seats/x-13-data/documentation/docx13as.pdf

Croson, R., & Gneezy, U. (2009). Gender differences in preferences. *Journal of Economic literature*, *47*(2), 448-474.

Di Maggio, M., Kermani, A., Keys, B. J., Piskorski, T., Ramcharan, R., Seru, A., & Yao, V. (2017). Interest rate pass-through: Mortgage rates, household consumption, and voluntary deleveraging. *American Economic Review*, *107*(11), 3550-3588.

Druedahl, J., Bjerre Jensen, E., & Leth-Petersen, S. (2022). The Intertemporal Marginal Propensity to Consume out of Future Persistent Cash-Flows. Evidence from Transaction Data. *Univ. of Copenhagen Dept. of Economics Discussion Paper*(13/22). https://www.econ.ku.dk/cebi/publikationer/working-papers/CEBI_WP_13-22.pdf

DSS. (2022). *Timeline: News from Norwegian Ministries about the Coronavirus disease Covid-19*. Norwegian Government Security and Service Organisation. Retrieved May 3, 2023 from https://www.regjeringen.no/en/topics/koronavirus-covid-19/timeline-for-news-from-norwegian-ministries-about-the-coronavirus-disease-covid-19/id2692402/

Duca, I., Kenny, G., & Reuter, A. (2019). Inflation Expectations, Consumption and the Lower Bound: Micro Evidence from a Large Euro Area Survey. *European Commission,*. https://doi.org/10.2765/844956

Fagereng, A., Holm, M. B., & Natvik, G. J. (2021). MPC Heterogeneity and Household Balance Sheets. *American Economic Journal: Macroeconomics*, *13*(4), 1-54. https://doi.org/10.1257/mac.20190211

Finansdepartementet. (2022). *The lending regulation*. Ministry of Finance. Retrieved April 17, 2023 from https://www.regjeringen.no/en/topics/the-economy/finansmarkedene/the-lending-regulation/id2950571/

Finanstilsynet. (2022a). *Boliglånsundersøkelsen 2022*. Finanstilsynet. Retrieved April 17, 2023 from https://www.finanstilsynet.no/publikasjoner-og-analyser/boliglansundersokelser/boliglansundersokelsen-2022/hovedside-for-boliglansundersokelsen-2022/boliglansundersokelsen-2022/

Finanstilsynet. (2022b). *Risk Outlook December 2022*. Finanstilsynet Retrieved from https://www.finanstilsynet.no/en/publications/risk-outlook-reports/

Flodén, M., Kilström, M., Sigurdsson, J., & Vestman, R. (2021). Household debt and monetary policy: revealing the cash-flow channel. *The Economic Journal*, *131*(636), 1742-1771. https://academic.oup.com/ej/article/131/636/1742/6039341

Forbrukerrådet. (2023). *Bytteundersøkelsen 2023 - Nordmenns byttevaner i 2022 innen finansielle tjenester*. https://storage02.forbrukerradet.no/media/2023/04/bytteundersokelsen-2023-1.pdf

Friedman, M. (1957). The permanent income hypothesis. In *A theory of the consumption function* (pp. 20-37). Princeton University Press.

Gerdrup, K. R., & Torstensen, K. N. (2018). *The Effect of Higher Interest Rates on Household Disposable Income and Consumption - a Static Analysis of the Cash-Flow Channel* (8283790323). https://norges-bank.brage.unit.no/norges-bank-xmlui/handle/11250/2558912

Greifer, N. (2023). *Matching Methods*. https://cran.r-project.org/web/packages/MatchIt/vignettes/matching-methods.html

Gulbrandsen, M. A. H. (2023). Gjør høy gjeld husholdningenes konsum mer sensitivt for økonomiske sjokk? En oversikt over empirisk litteratur basert på mikrodata.

Norges Bank. https://www.norges-bank.no/aktuelt/nyheter-og-hendelser/Signerte-publikasjoner/Staff-Memo/20232/sm-3-2023/

Hayes, A. (2022). *What Is Variable Rate Mortgage? Benefits and Downsides*. Investopedia. Retrieved May 26, 2023 from https://www.investopedia.com/terms/v/variable-rate-mortgage.asp

Ho, D. E., Imai, K., King, G., & Stuart, E. A. (2011). *MatchIt: Nonparametric Preprocessing for Parametric Causal Inference*. In Journal of Statistical Software.

Holm, M. B., Paul, P., & Tischbirek, A. (2021). The Transmission of Monetary Policy under the Microscope. *Journal of Political Economy*, *129*(10), 2861-2904. https://doi.org/10.1086/715416

Jappelli, T., & Pistaferri, L. (2010). The Consumption Response to Income Changes. *Annual Review of Economics*, *2*(1), 479-506. https://doi.org/10.1146/annurev.economics.050708.142933

Jappelli, T., & Scognamiglio, A. (2018). Interest rate changes, mortgages, and consumption: evidence from Italy. Economic Policy, 33(94), 183-224.

Kimball, M., & Weil, P. (2009). Precautionary Saving and Consumption Smoothing across Time and Possibilities. *Journal of Money, Credit and Banking*, *41*(2/3), 245-284. http://www.jstor.org/stable/25483489

Koronakommisjonen. (2021). *NOU 6: Myndighetenes håndtering av koronapandemien - del 1*. Departementenes sikkerhets- og serviceorganisasjon Retrieved from https://www.koronakommisjonen.no/

Koronakommisjonen. (2022). *NOU 5: Myndighetenes håndtering av koronapandemien - del 2*. Departementenes sikkerhets- og serviceorganisasjon Retrieved from https://www.koronakommisjonen.no/

Krugman, P. R., Obstfeld, M., & Melitz, M. J. (2018). *International Economics: Theory and Policy* (Vol. Eleventh Edition). Pearson Education Limited.

Lycke, R. S. E. (2020, March 7, 2020). *Unge kvinner tar styringen på privatøkonomien*. SpareBank 1 SR-Bank. https://www.sparebank1.no/nb/sr-bank/om-oss/nyheter/unge-kvinner-tar-styringen-pa-privatokonomien.html

Norges Bank. (2021a). *Monetary Policy Report with financial stability assessment 1/2021*. Norges Bank Retrieved from https://www.norges-bank.no/en/news-events/news-publications/Reports/Monetary-Policy-Report-with-financial-stability-assessment/2021/mpr-12021/

Norges Bank. (2021b). *Monetary Policy Report with financial stability assessment 2/2021*. Norges Bank Retrieved from https://www.norges-bank.no/en/news-events/news-publications/Reports/Monetary-Policy-Report-with-financial-stability-assessment/2021/mpr-22021/

Norges Bank. (2021c). *Monetary Policy Report with financial stability assessment 4/2021*. Norges Bank Retrieved from https://www.norges-bank.no/en/news-events/news-publications/Reports/Monetary-Policy-Report-with-financial-stability-assessment/2021/mpr-42021/

Norges Bank. (2021d). *Norges Bank's monetary policy strategy statement*. Norges Bank. Retrieved May 12, 2023 from https://www.norges-bank.no/en/topics/Monetary-policy/monetary-policy-strategy/

Norges Bank. (2022a, March 24, 2022). *The countercyclical capital buffer will be raised to 2.5 percent* https://www.norges-bank.no/en/news-events/news-publications/Press-releases/2022/2022-03-24-ccb/

Norges Bank. (2022b). *Financial Stability Report 2022: vulnerabilities and risks*. Norges Bank Retrieved from https://www.norges-bank.no/en/news-events/news-publications/Reports/Financial-Stability-report/2022-financial-stability-report/

Norges Bank. (2022c). *Monetary Policy Report with financial stability assessment 1/2022*. Norges Bank Retrieved from https://www.norges-bank.no/en/news-events/news-publications/Reports/Monetary-Policy-Report-with-financial-stability-assessment/2022/mpr-12022/

Norges Bank. (2022d). Norges Bank's Monetary Policy Handbook 1/2022. *Norges Bank Papers*. https://www.norges-bank.no/en/news-events/news-publications/Reports/Norges-Bank-Papers/2022/memo-12022-monetary-policy-handbook/

Norges Bank. (2023). *The policy rate*. Norges Bank. Retrieved April 13, 2023 from https://www.norges-bank.no/en/topics/Monetary-policy/Policy-rate/

OECD. (2023). *Household debt (indicator)* https://doi.org/10.1787/f03b6469-en

Olsen, Ø. (2020). *The role of monetary policy during the Covid-19 pandemic*. Norges Bank. Retrieved May 4, 2023 from https://www.norges-bank.no/en/news-events/news-publications/Speeches/2020/2020-10-06-cme/

Pemberton, J. (1997). The Empirical Failure of the Life Cycle Model with Perfect Capital Markets. *Oxford Economic Papers*, *49*(2), 129-151. http://www.jstor.org/stable/2663734

Reiche, L., & Meyler, A. (2022). Making sense of consumer inflation expectations: the role of uncertainty. *European Commission*. https://doi.org/10.2765/328023

Romer, C. D., & Romer, D. H. (2004). A new measure of monetary shocks: Derivation and implications. *American Economic Review*, *94*(4), 1055-1084.

Romer, D. H. (2019). *Advanced Macroeconomics* (Vol. 5th Edition). McGraw-Hill Education.

Sahm, C. R. (2012). How Much Does Risk Tolerance Change? *Quarterly Journal of Finance*, *02*(04), 1250020. https://doi.org/10.1142/s2010139212500206

Statistics Norway. (2022). *Økt formue og boligformue blant eldre*. Statistics Norway. Retrieved May 24, 2023 from https://www.ssb.no/inntekt-og-forbruk/inntekt-og-formue/artikler/okt-formue-og-boligformue-blant-eldre

Statistics Norway. (2023a). *05277: Population and land area in urban settlements* https://www.ssb.no/en/statbank/table/05277/

Statistics Norway. (2023b). *07221: Price for existing dwellings, by type of building and region (2015=100) 1992K1 - 2023K1* https://www.ssb.no/en/statbank/table/07221/

Statistics Norway. (2023c). *07459: Population* https://www.ssb.no/en/statbank/table/07459/

Statistics Norway. (2023d). *09477: Financial accounts. Houshold rates (per cent) 1996K4 - 2022K4* https://www.ssb.no/en/statbank/table/09477/

Statistics Norway. (2023e). *10648: Interest rates and the belonging loan amount, by type of loan, sector and fixed-rate period. Complete census 2013K4 - 2023K1* https://www.ssb.no/en/statbank/table/10648

Statistics Norway. (2023f). *10746: Interest rates on outstanding repayment loans, by type of loan, sector and fixed-rate period. Sample of banks and mortgage companies (per cent) 2013M12 - 2023M02* https://www.ssb.no/en/statbank/table/10746/

Statistics Norway. (2023g). *11032: Housing conditions, register-based* https://www.ssb.no/en/statbank/table/11032/

Statistics Norway. (2023h). *11721: Final expenditure and gross domestic product. Unadjusted and seasonally adjusted figures 2016M01 - 2023M02* https://www.ssb.no/en/statbank/table/11721/

Statistics Norway. (2023i). *13760: Labour force survey* https://www.ssb.no/en/statbank/table/13760

The Norwegian Directorate of Health. (2022). *Befolkningsundersøkelse covid-19*. https://www.helsedirektoratet.no/tema/beredskap-og-krisehandtering/koronavirus/befolkningsundersokelse-covid-19

World Bank. (2022). *World Development Report 2022: Finance for an equitable recovery*. The World Bank. https://www.worldbank.org/en/publication/wdr2022

Yagihashi, T., & Du, J. (2015). Intertemporal elasticity of substitution and risk aversion: are they related empirically? *Applied Economics*, *47*(15), 1588-1605. https://doi.org/10.1080/00036846.2014.1000530

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Appendix 1: Descriptive Statistics

Table 5: Description of Variables

Variable type	Variable name	Description
Continuous	*Total loans*	Total loans include mortgages, home equity loans and equity release mortgages.
	LTV	Loan-to-value ratio on a customer's total loans.
	Consumption	The consumption measure includes debit card transactions, cash withdrawal and VIPPS transactions.
	Consumption seasonally adjusted	Aggregated consumption seasonally adjusted employing the X-13ARIMA-SEATS method implemented in R by Center for Statistical Research and Methodology (2017).
	Loan interest rate	The customer's average monthly interest rate on total loans.
	Unemployment rate	Seasonally adjusted total unemployment in percent of the workforce retrieved from Statistics Norway (2023i).
Categorical	*Age group*	Age groups are divided as follows: *0 to 25 years* *26 to 45 years* *46 to 65 years* *66 years and older*
Categorical	*Relative LTV*	Relative loan-to-value ratio in relation to the above age groups. Percentile divided as follows: *Extremely low* *2nd to 20th percentile [Robust group]* *20th to 30th percentile* *30th to 40th percentile* *40th to 50th percentile* *50th to 60th percentile* *60th to 70th percentile* *70th to 80th percentile* *80th to 98th percentile [Exposed group]* *Extremely high*
	Region	The customer's residing region, defined by counties as follows: *Central Norway*: Møre og Romsdal and Trøndelag *Northern Norway:* Troms og Finnmark and Nordland *Oslo*: Oslo *Remaining South-Eastern Norway:* Agder, Vestfold og Telemark, Innlandet, and Viken *Western Norway:* Vestland and Rogaland
Dummy	*Gender*	Male, Female

Large Urban Area	The customer is residing in a settlement with more than 100,000 inhabitants, which includes the following municipalities: *Oslo, Bærum, Asker, Lillestrøm, Lørenskog, Nordre Follo, Rælingen, Nittedal, Lier, Bergen, Stavanger, Sandnes, Sola, Randaberg, Trondheim, Fredrikstad, Sarpsborg, Drammen, Øvre Eiker,* and *Holmestrand*. Retrieved from Statistics Norway (2023a).
Large Buffer	The customer holds deposits, including checking and savings account, exceeding 200,000 NOK. Corresponding approximately to the highest quintile of the deposits in the sample.
Private sector	The customer is occupied in private sector.
Public sector	The customer is occupied in public sector
Retired	The customer is defined as retired if her age is greater than 67 years.
Co-dependency	The customer is defined as co-dependent if she has a co-borrower.
Debt Expander	The customer is defined as debt expander if the mean total loans increase with more than 1 percent from the pre-treatment to the post-treatment period.

Note:
Unless otherwise stated, the variables are obtained from BN Bank.

Table 6: Descriptive Statistics for Treatment Groups: Hike Period

	Exposed individuals (N=962)	Robust individuals (N=1103)
Consumption (NOK)		
Mean (SD)	17,000 (± 8,000)	15,900 (± 7,800)
Median [Min / Max]	16,400 [0 / 41,000]	15,000 [0 / 42,300]
Deposits (NOK)		
Mean (SD)	143,700 (± 351,800)	295,800 (± 488,200)
Median [Min / Max]	44,800 [0 / 7,084,800]	127,000 [0 / 6,063,600]
Loan interest rate		
Mean (SD)	2.23 (± 0.37)	2.07 (± 0.29)
Median [Min / Max]	2.17 [1.01 / 3.51]	2.05 [0.89 / 3.4]
LTV ratio		
Mean (SD)	0.71 (± 0.1)	0.24 (± 0.12)
Median [Min / Max]	0.72 [0.28 / 0.86]	0.22 [0.03 / 0.48]
Loan size (EAD)		
Mean (SD)	3,260,600 (± 1,610,600)	1,580,700 (± 1,338,000)
Median [Min / Max]	2,908,000 [147,200 / 9,817,900]	1,164,400 [41,600 / 8,906,600]
Large buffer (1 = yes)		
Mean (SD)	0.23 (± 0.42)	0.44 (± 0.5)
Median [Min / Max]	0 [0 / 1]	0 [0 / 1]
Debt expander (1 = yes)		
Mean (SD)	0.09 (± 0.29)	0.05 (± 0.21)
Median [Min / Max]	0 [0 / 1]	0 [0 / 1]
Occupation		
Private sector	653 (68 %)	534 (48 %)
Public sector	122 (13 %)	177 (16 %)
Retired	131 (14 %)	218 (20 %)
Self-employed	30 (3 %)	25 (2 %)
Missing	26 (2.7%)	149 (13.5%)
Co-dependent (1 = yes)		
Mean (SD)	0.61 (± 0.49)	0.51 (± 0.5)
Median [Min / Max]	1 [0 / 1]	1 [0 / 1]
Age (years)		
Mean (SD)	51.38 (± 12.82)	54.22 (± 14.21)
Median [Min / Max]	50 [26 / 90]	54 [26 / 93]
Gender		
Female	294 (31 %)	454 (41 %)
Male	668 (69 %)	649 (59 %)
Large Urban Area (1 = yes)		
Mean (SD)	0.67 (± 0.47)	0.8 (± 0.4)
Median [Min / Max]	1 [0 / 1]	1 [0 / 1]

Note:
See appendix 1, Table 5 for a full description of the variables. Based on the period September 30, 2021, until March 31, 2022. Continuous values greater than 1,000 are rounded to the nearest hundred, while values that are less are rounded to the nearest two decimal places.

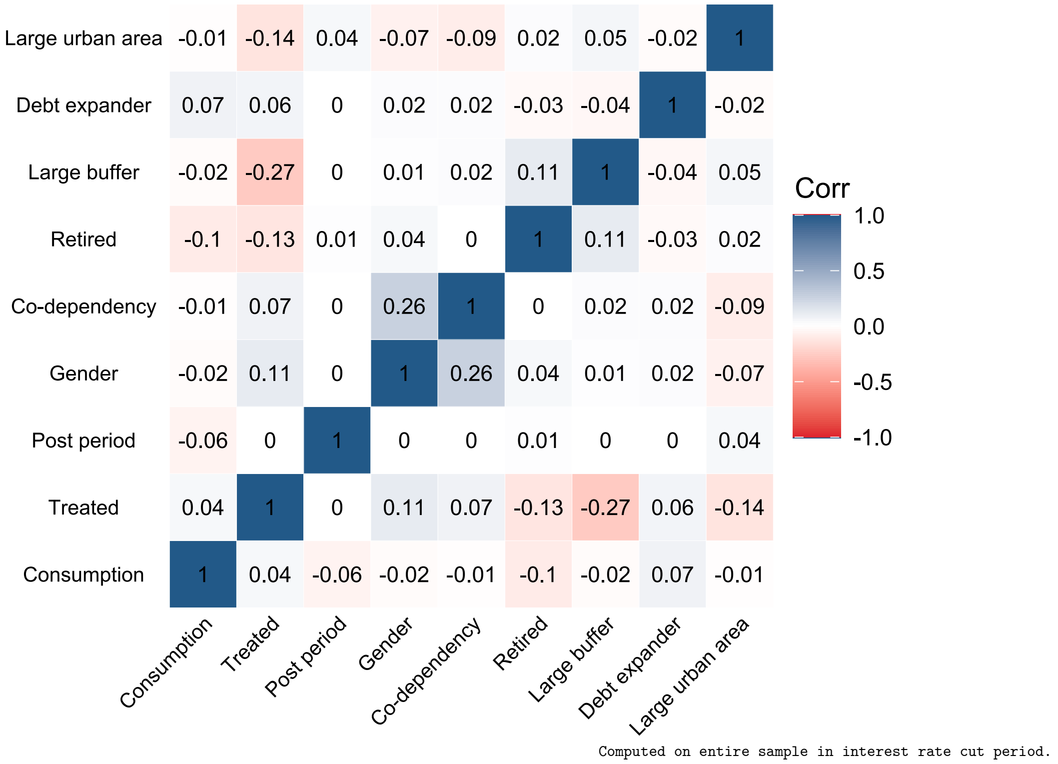

Figure 10: Correlation Coefficient Matrix – Cut Period

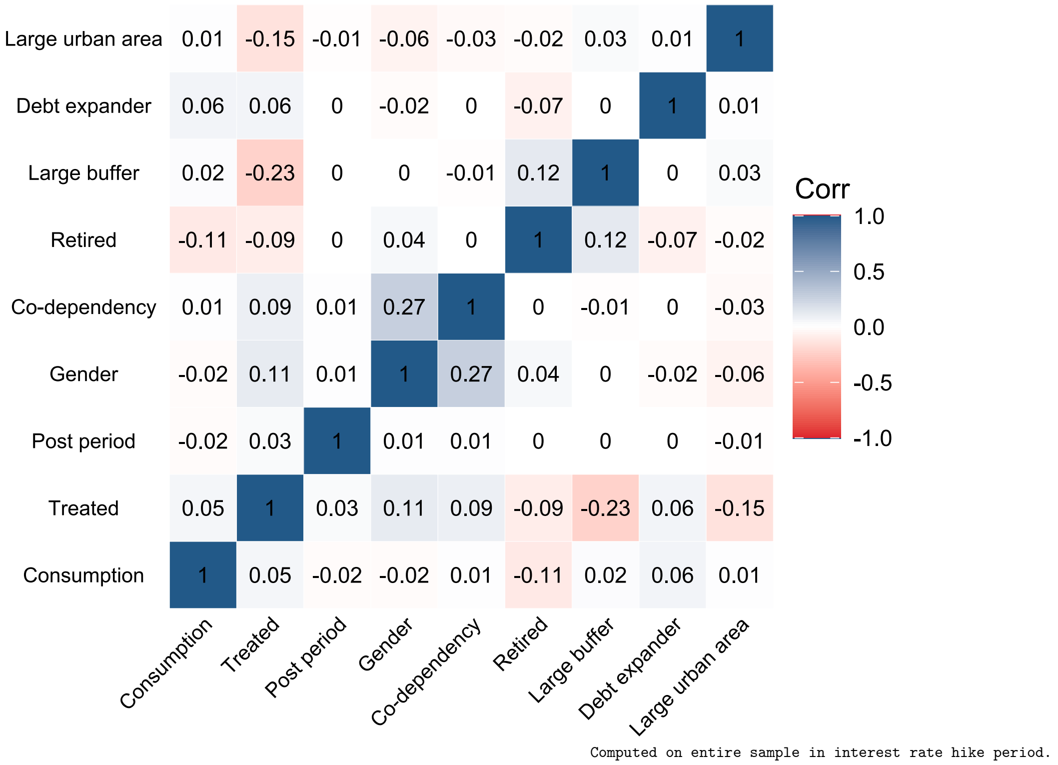

Figure 11: Correlation Coefficient Matrix – Hike Period

Appendix 2: Additional Regression Results

Table 7: Regression Results - Optimal Pair Matching - Cut Period

	Dependent variable:			
	Log(Consumption)			
	(1)	(2)	(3)	(4)
Exposed	-0.0001	-0.005	-0.024	-0.022
	(0.030)	(0.030)	(0.030)	(0.031)
Post period	-0.148***	-0.174***	-0.174***	-0.242***
	(0.030)	(0.033)	(0.033)	(0.053)
*Exposed * Post period*	0.080*	0.080*	0.079*	0.074*
	(0.044)	(0.043)	(0.043)	(0.045)
Specified as in main model	Yes	Yes	Yes	Yes
Observations	8,006	8,006	8,006	8,006
R^2	0.004	0.011	0.015	0.016
Adjusted R^2	0.003	0.010	0.014	0.014
Residual Std. Error	0.977 (df = 8002)	0.974 (df = 7998)	0.972 (df = 7995)	0.972 (df = 7990)
F Statistic	10.369*** (df = 3; 8002)	12.499*** (df = 7; 7998)	12.356*** (df = 10; 7995)	8.607*** (df = 15; 7990)

Note:
*p<0.1; **p<0.05; ***p<0.01
Pre-treatment period from December 1, 2019, to February 29, 2020.
Post-treatment period from March 1, 2020, to May 31, 2020.
See Table 3 and Table 4 for main model specifications.

Table 8: Regression Results - Optimal Pair Matching - Hike Period

	Dependent variable:			
	Log(Consumption)			
	(1)	(2)	(3)	(4)
Exposed	0.054*	0.048	0.059**	0.065**
	(0.029)	(0.029)	(0.030)	(0.031)
Post period	-0.036	-0.035	-0.034	-0.070
	(0.027)	(0.027)	(0.027)	(0.052)
*Exposed * Post period*	0.007	0.006	0.004	-0.008
	(0.039)	(0.039)	(0.039)	(0.041)
Specified as in main model	Yes	Yes	Yes	Yes
Observations	10,476	10,476	10,476	10,476
R^2	0.001	0.006	0.009	0.011
Adjusted R^2	0.001	0.006	0.008	0.009
Residual Std. Error	0.980 (df = 10472)	0.978 (df = 10469)	0.976 (df = 10466)	0.976 (df = 10461)
F Statistic	3.823*** (df = 3; 10472)	10.773*** (df = 6; 10469)	10.558*** (df = 9; 10466)	7.933*** (df = 14; 10461)

Note:
*p<0.1; **p<0.05; ***p<0.01
Pre-treatment period from September 1, 2021, to November 30, 2021.
Post-treatment period from December 1, 2021, to March 31, 2022.
See Table 3 and Table 4 for main model specifications.

Table 9: Regression Results - Generalized Full Matching - Cut Period

	Dependent variable:			
	Log(Consumption)			
	(1)	(2)	(3)	(4)
Exposed	-0.047	-0.046	-0.055*	-0.055*
	(0.032)	(0.032)	(0.032)	(0.033)
Post period	-0.144***	-0.175***	-0.175***	-0.253***
	(0.035)	(0.038)	(0.038)	(0.058)
*Exposed * Post period*	0.079*	0.078*	0.077*	0.078
	(0.046)	(0.046)	(0.046)	(0.048)
Specified as in main model	Yes	Yes	Yes	Yes
Observations	8,495	8,495	8,495	8,495
R^2	0.003	0.008	0.011	0.012
Adjusted R^2	0.003	0.007	0.009	0.010
Residual Std. Error	0.985 (df = 8491)	0.983 (df = 8487)	0.982 (df = 8484)	0.982 (df = 8479)
F Statistic	8.835*** (df = 3; 8491)	9.491*** (df = 7; 8487)	9.022*** (df = 10; 8484)	6.582*** (df = 15; 8479)

Note:
*p<0.1; **p<0.05; ***p<0.01
Pre-treatment period from December 1, 2019, to February 29, 2020.
Post-treatment period from March 1, 2020, to May 31, 2020.
See Table 3 and Table 4 for main model specifications.

Table 10: Regression Results - Generalized Full Matching - Hike Period

	Dependent variable:			
	Log(Consumption)			
	(1)	(2)	(3)	(4)
Exposed	0.026	0.027	0.041	0.046
	(0.030)	(0.030)	(0.030)	(0.031)
Post period	-0.049*	-0.049*	-0.049*	-0.111**
	(0.030)	(0.029)	(0.029)	(0.055)
*Exposed * Post period*	0.021	0.020	0.019	0.010
	(0.040)	(0.040)	(0.040)	(0.042)
Specified as in main model	Yes	Yes	Yes	Yes
Observations	11,426	11,426	11,426	11,426
R^2	0.001	0.006	0.009	0.011
Adjusted R^2	0.001	0.005	0.009	0.010
Residual Std. Error	0.980 (df = 11422)	0.978 (df = 11419)	0.976 (df = 11416)	0.975 (df = 11411)
F Statistic	3.009** (df = 3; 11422)	11.066*** (df = 6; 11419)	12.057*** (df = 9; 11416)	9.322*** (df = 14; 11411)

Note:
*p<0.1; **p<0.05; ***p<0.01
Pre-treatment period from September 1, 2021, to November 30, 2021.
Post-treatment period from December 1, 2021, to March 31, 2022.
See Table 3 and Table 4 for main model specifications.

Table 11: Regression Results – Two-Way Fixed Effects DiD

	Dependent variable:	
	Log(Consumption)	
	Cut Period	Hike Period
*Exposed * Post Period*	0.076*	0.018
	(0.042)	(0.039)
Group Fixed Effects	Yes	Yes
Time Fixed Effects	Yes	Yes
Control variables	No	No
Observations	8,495	10,476
R^2	0.018	0.009
Adjusted R^2	0.017	0.008
Residual Std. Error	0.980 (df = 8487)	0.975 (df = 10467)
F Statistic	22.040*** (df = 7; 8487)	12.004*** (df = 8; 10467)

Note:
*p<0.1; **p<0.05; ***p<0.01
Interest rate cut period:
Pre-treatment period from December 1, 2019, to February 29, 2020.
Post-treatment period from March 1, 2020, to May 31, 2020.
Interest rate hike period:
Pre-treatment period from September 1, 2021, to November 30, 2021.
Post-treatment period from December 1, 2021 to March 31, 2022.

Table 12: Regression Results - Placebo Treatment Periods

	Dependent variable:	
	Log(Consumption)	
	Time period 1	Time period 2
Exposed	0.026	0.047**
	(0.027)	(0.021)
Post period	0.042	-0.151***
	(0.039)	(0.033)
*Exposed * Post period*	-0.032	-0.003
	(0.038)	(0.029)
Specified as model 4 in main model	Yes	Yes
Observations	9,909	18,877
R^2	0.014	0.017
Adjusted R^2	0.012	0.016
Residual Std. Error	0.909 (df = 9896)	0.955 (df = 18864)
F Statistic	11.298*** (df = 12; 9896)	26.626*** (df = 12; 18864)

Note:
*p<0.1; **p<0.05; ***p<0.01
Time period 1:
Pre-treatment: March 1, 2017, to June 30, 2017.
Post-treatment: July 1, 2017, to October 31, 2017.
Time period 2:
Pre-treatment: July 1, 2020, to December 31, 2020.
Post-treatment: January 1, 2021, to June 30, 2021.
See Table 3 and Table 4 for main model specifications.

Table 13: Regression Results - Interaction Tests - Cut Period

	Dependent variable:		
	Log(Consumption)		
	(1)	(2)	(3)
Exposed	-0.032	-0.046	-0.034
	(0.031)	(0.031)	(0.031)
Post period	-0.279***	-0.206***	-0.224***
	(0.056)	(0.057)	(0.057)
*Exposed * Post period*	0.082*	0.094**	0.087*
	(0.044)	(0.045)	(0.045)
Co-dependent	-0.069***	-0.063**	-0.031
	(0.022)	(0.030)	(0.031)
Gender	-0.123***		-0.133***
	(0.029)		(0.030)
*Post * Gender*	0.074*		0.094**
	(0.042)		(0.044)
*Post * Co-dependent*		-0.054	-0.077*
		(0.043)	(0.044)
Specified as main model	Yes	Yes	Yes
Observations	8,495	8,495	8,495
R^2	0.016	0.014	0.015
Adjusted R^2	0.014	0.012	0.014
Residual Std. Error	0.982 (df = 8479)	0.983 (df = 8480)	0.982 (df = 8479)
F Statistic	8.990*** (df = 15; 8479)	8.529*** (df = 14; 8480)	8.823*** (df = 15; 8479)

Note:
*p<0.1; **p<0.05; ***p<0.01
Pre-treatment period from December 1, 2019, to February 29, 2020.
Post-treatment period from March 1, 2020, to May 31, 2020.
See Table 3 and Table 4 for main model specifications.

Table 14: Regression Results - Interaction Tests - Hike Period

	Dependent variable:		
	Log(Consumption)		
	(1)	(2)	(3)
Exposed	0.053*	0.047	0.053*
	(0.030)	(0.030)	(0.030)
Post period	-0.080	-0.084*	-0.077
	(0.049)	(0.049)	(0.052)
*Exposed * Post period*	0.002	0.003	0.003
	(0.040)	(0.039)	(0.040)
Co-dependent	-0.003	-0.011	0.003
	(0.018)	(0.028)	(0.028)
Gender	-0.052*		-0.054*
	(0.030)		(0.029)
*Post * Gender*	-0.015		-0.012
	(0.039)		(0.039)
*Post * Co-dependent*		-0.012	-0.010
		(0.037)	(0.037)
Specified as main model	Yes	Yes	Yes
Observations	11,426	11,426	11,426
R^2	0.011	0.010	0.011
Adjusted R^2	0.010	0.009	0.010
Residual Std. Error	0.972 (df = 11411)	0.972 (df = 11412)	0.972 (df = 11410)
F Statistic	9.040*** (df = 14; 11411)	8.996*** (df = 13; 11412)	8.441*** (df = 15; 11410)

Note:
*p<0.1; **p<0.05; ***p<0.01
Pre-treatment period from September 1, 2021, to November 30, 2021.
Post-treatment period from December 1, 2021, to March 31, 2022.
See Table 3 and Table 4 for main model specifications.

Table 15: Regression Results – Placebo Treatment Groups - Cut Period

	Dependent variable:			
	Log(Consumption)			
	(1)	(2)	(3)	(4)
Exposed	-0.027	-0.024	-0.021	-0.022
	(0.040)	(0.040)	(0.040)	(0.040)
Post period	-0.092**	-0.133***	-0.135***	-0.136**
	(0.041)	(0.043)	(0.043)	(0.064)
*Exposed * Post period*	0.020	0.019	0.017	0.019
	(0.056)	(0.056)	(0.056)	(0.056)
Specified as main model	Yes	Yes	Yes	Yes
Observations	5,160	5,160	5,160	5,160
R^2	0.002	0.005	0.006	0.006
Adjusted R^2	0.001	0.004	0.004	0.004
Residual Std. Error	1.007 (df = 5156)	1.005 (df = 5153)	1.005 (df = 5150)	1.005 (df = 5147)
F Statistic	3.001** (df = 3; 5156)	4.180*** (df = 6; 5153)	3.546*** (df = 9; 5150)	2.777*** (df = 12; 5147)

Note:
*p<0.1; **p<0.05; ***p<0.01
Pre-treatment period from December 1, 2019, to February 29, 2020.
Post-treatment period from March 1, 2020, to May 31, 2020
Exposed defined as relative LTV between 50th and 60th percentile
Robust defined as relative LTV between 40th and 50th percentile.
See Table 3 and Table 4 for main model specifications.

Table 16: Regression Results – Placebo Treatment Groups - Hike Period

	Dependent variable:			
	Log(Consumption)			
	(1)	(2)	(3)	(4)
Exposed	0.002	0.004	0.008	0.008
	(0.033)	(0.033)	(0.033)	(0.033)
Post period	-0.027	-0.025	-0.026	-0.035
	(0.030)	(0.030)	(0.030)	(0.054)
*Exposed * Post period*	-0.027	-0.031	-0.033	-0.032
	(0.044)	(0.044)	(0.044)	(0.044)
Specified as main model	Yes	Yes	Yes	Yes
Observations	7,807	7,807	7,807	7,807
R^2	0.001	0.007	0.009	0.009
Adjusted R^2	0.0001	0.006	0.008	0.007
Residual Std. Error	0.965 (df = 7803)	0.962 (df = 7801)	0.961 (df = 7798)	0.961 (df = 7795)
F Statistic	1.341 (df = 3; 7803)	10.412*** (df = 5; 7801)	8.709*** (df = 8; 7798)	6.348*** (df = 11; 7795)

Note:
*p<0.1; **p<0.05; ***p<0.01
Pre-treatment period from September 1, 2021, to November 30, 2021.
Post-treatment period from December 1, 2021, to March 31, 2022.
Exposed defined as relative LTV between 50th and 60th percentile.
Robust defined as relative LTV between 40th and 50th percentile.
See Table 3 and Table 4 for main model specifications.

Appendix 3: Descriptive Matching Statistics

Table 17: Summary of Balance for Entire Sample

	Means Treated	Means Control	Std. Mean Diff.	Var. Ratio
Distance	0.57	0.48	0.62	0.87
Male (1 = yes)	0.34	0.45	-0.23	
Female (1 = yes)	0.66	0.55	0.23	
Large Urban Area (1 = yes)	0.58	0.71	-0.26	
Private sector	0.71	0.46	0.54	
Retired	0.08	0.16	-0.3	
Co-dependent (1 = yes)	0.58	0.52	0.13	

Note:
Sample consisting of control and treatment during the period of December 1, 2019, until May 31, 2020.

Table 18: Summary of Balance for Optimal Pair Matched Data

	Means treated	Means control	Std. Mean diff.	Var. Ratio
Distance	0.55	0.48	0.47	0.79
Male (1 = yes)	0.38	0.45	-0.15	
Female (1 = yes)	0.62	0.55	0.15	
Large Urban Area (1 = yes)	0.65	0.71	-0.11	
Private sector	0.67	0.46	0.46	
Retired	0.09	0.16	-0.27	
Co-dependent (1 = yes)	0.54	0.52	0.05	

Note:
Sample consisting of control and treatment during the period of December 1, 2019, until May 31, 2020.

Table 19: Summary of Balance for Generalized Full Matched Data

	Means treated	Means control	Std. Mean diff.	Var. Ratio
Distance	0.57	0.57	-0	0.9999
Male (1 = yes)	0.34	0.34	0	
Female (1 = yes)	0.66	0.66	0	
Large Urban Area (1 = yes)	0.58	0.58	0	
Private sector	0.71	0.71	0	
Retired	0.08	0.08	0	
Co-dependent (1 = yes)	0.58	0.58	0	

Note:
Sample consisting of control and treatment during the period of December 1, 2019, until May 31, 2020.

Table 20: Sample Sizes

	Optimal Pair Matching		*Generalized Full Matching*	
	Control	Treated	Control	Treated
All	4003	4492	4003	4492
Matched (ESS)	4003	4003	2861	4492
Matched	4003	4003	4003	4492
Unmatched	0	489	0	0
Discarded	0	0	0	0

Note:
Sample consisting of control and treatment during the period of December 31, 2019, until May 31, 2020.
ESS = Effective sample size

Appendix 4: Example Calculations

Table 21: Loan Specific Statistics

Period	Group	Number of individuals	Consumption (NOK)	Principal (NOK)	Loan's remaining terms (years)
Interest rate cut period	Robust	599	13,945	1,300,182	16.6
	Exposed	679	14,588	2,858,819	26.5
Interest rate hike period	Robust	845	15,662	1,454,363	17.6
	Exposed	769	16,280	3,133,583	26.0

Note:
The table contains computed mean values for the control and treatment group in each period.
Individuals characterized as debt expanders and those with interest-only mortgages are omitted from the sample.
For simplicity, the principal is defined as the mean value for all loans in the period, also including home equity loans, equity release mortgages, and interest-only loans.
Remaining terms weighted on all loans.

Table 22: Computed DiD Estimates

Period	Group	Treatment period	Loan interest rate	Interest expenses (NOK)		Principal payment (NOK)		Total payment (NOK)	Change in total payment (NOK)	Change in loan interest rate (percentage points)	Difference in change in total payment (NOK)	Computed DiD estimate
Interest rate cut period	Robust	Pre	3.13%	3,390	+	4,972	=	8,362	-446	-0.71%	-353	2.21%
		Post	2.42%	2,620	+	5,296	=	7,916				
	Exposed	Pre	3.35%	7,975	+	5,608	=	13,584	-799	-0.53%		
		Post	2.82%	6,716	+	6,069	=	12,785				
Interest rate hike period	Robust	Pre	1.90%	2,302	+	5,791	=	8,093	225	0.33%	253	-1.52%
		Post	2.23%	2,701	+	5,616	=	8,317				
	Exposed	Pre	2.07%	5,396	+	7,613	=	13,009	478	0.31%		
		Post	2.37%	6,197	+	7,290	=	13,487				

Note:
The table contains calculations of a highly simplified example which complies with the DiD estimate from the regression results.
The computed DiD estimate is the percentage difference in consumption between groups given that the whole change in disposable income is used on consumption (MPC = 1).
We make the assumption that the principal and the loan's remaining terms do not change between periods.
The interest expenses, the principal payment and the total payment amount are calculated with a standard annuity formula.