Master's thesis

NTNU
Norwegian University of Science and Technology
Faculty of Economics and Management
Department of Economics

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Short-run Heterogeneity in Consumption Responses to Interest Rate Changes

An Approach Using Microdata from a Norwegian Bank

Master's thesis in Economics
Supervisor: Endre Jo Reite
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Abstract

The households' short-run consumption response to interest rate changes is scarcely researched in the existing literature. Employing administrative data on mortgagors from BN Bank, this thesis examines the role of financial robustness on consumption responses. We take advantage of the sudden interest rate cut caused by the COVID-19 pandemic in the spring of 2020 and the subsequent interest rate hike during the winter of 2021-22. In the analysis, we employ a difference-in-difference research design comparing financially robust and exposed individuals, measured by their loan-to-value ratio relative to their age group. We estimate the level of heterogeneity between the two groups in short-term consumption responses to interest rate changes. We find support for the cash flow channel during the interest rate cut period, in line with previous research. However, compared to calculations of the actual cash flow, we overestimate the effect. During the interest rate hike period, we find no significant differences in consumption development between the two groups. This is not in accordance with the cash flow channel and is asymmetric to the results following the interest rate cut. In addition to the cash flow channel, we highlight the effect of risk aversion heterogeneity, under which the precautionary savings and the substitution channels are plausible explanatory factors. This study's primary contribution lies in the approach used on a novel dataset, examining the short-run consumption responses to interest rate changes. Ultimately, this study provides a useful foundation for further research. Increased knowledge about heterogeneity in short-term consumption responses to interest rate changes may have implications for monetary policy conduction.

Sammendrag

Husholdningenes kortsiktige konsumrespons ved renteendringer er lite utforsket i den eksisterende litteraturen. Ved å benytte administrativ data på boliglånskunder fra BN Bank, undersøker vi i denne masteroppgaven konsumresponsen ved renteendringer. Vi utnytter det brå rentekuttet forårsaket av koronapandemien våren 2020, samt den påfølgende renteøkningen vinteren 2021-22. I analysen benytter vi en difference-in-differences estimeringsstrategi der vi sammenligner finansielt robuste og utsatte individer, målt etter deres belåningsgrad i forhold til deres aldersgruppe. Vi estimerer nivået av heterogenitet i den kortsiktige konsumresponsen etter renteendringer. I tråd med tidligere forskning finner vi støtte for den kortsiktige kontantstrømkanalen i rentereduksjonsperioden. Sammenlignet med kalkulasjoner på den faktiske kontantstrømmen overestimerer vi imidlertid effekten. I løpet av renteøkningsperioden finner vi ingen signifikant forskjell i forbruksutviklingen. Dette er ikke i samsvar med kontantstrømkanalen og er asymmetrisk i forhold til resultatene for rentereduksjonsperioden. I tillegg til kontantstrømkanalen fremhever vi heterogenitet i risikoaversjon, der forsiktighetssparing- og substitusjons-kanalen er plausible forklaringsfaktorer for resultatene. Det primære bidraget til denne studien ligger i tilnærmingen benyttet på et uutforsket datasett, der vi undersøker den kortsiktige konsumresponsen ved renteendringer. Denne studien gir et nyttig grunnlag for videre forskning. Økt kunnskap om heterogenitet i kortsiktige konsumresponser ved renteendringer kan ha implikasjoner for pengepolitikken.

Acknowledgments

This master's thesis marks the end of five years of studies in Trondheim at the Department of Economics for both of us. Writing this master's thesis has been a demanding and enriching process. We look forward to bringing the experiences with us into the next chapter of our lives.

First and foremost, we would like to thank our supervisor and mentor, Endre Jo Reite. The guidance he has provided us has been incredibly valuable. His insights have always been spot-on, and we have enjoyed our time working with him. We would also like to thank BN Bank ASA for a rewarding cooperation and, specifically, the people in the Risk & Compliance department for valuable advice and a shoulder to lean on.

We thank our fellow students for making the time in Trondheim a pleasure. Their company has made the process of writing this thesis much more enjoyable. Finally, we would like to thank our family for their love and support during the past five years and during the work on this thesis.

Tobias Gamrath & Øystein Sand
Trondheim, June 1, 2023

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1 Introduction

Understanding the channels through which interest rates affect private consumption is essential to explain the transmission mechanisms of monetary policy properly. The purpose of this study is to analyze short-run heterogeneity in consumption responses following interest rate changes. Specifically, we wish to estimate how financial robustness affects the level of heterogeneity.

We base our study on the hypothesis that financially exposed individuals change their consumption more following an interest rate change compared to financially robust individuals. This is in line with the theoretical cash flow channel, which describes how an interest rate change leads to a change in interest expenses or income and, thus, disposable income, which again transfers to consumption. Individuals with different levels of indebtedness will experience different disposable income effects. This suggests heterogeneity in consumption responses between 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-run effects of the cash flow channel are researched thoroughly using administrative register data, and several studies show a significant difference between how financially exposed and financially robust groups adapt to interest rate changes. However, research focusing on short-term heterogeneous effects is still rare in existing literature, likely because of insufficient data access. We offer an alternative and novel approach using microdata from BN Bank, a small nationwide Norwegian bank, with monthly observations to estimate the short-term effects of interest rate shocks on heterogeneity in consumption responses.

By accessing administrative data from a bank and analyzing heterogeneous short-term interest effects on private consumption, we perform research that is rare in the existing literature. Our dataset is novel in that it has not previously been employed to conduct macroeconomic analysis. Additionally, our approach is interesting in its focus on the short-term effects of heterogeneity in financial vulnerability. This has received little attention in the existing literature. Moreover, we analyze both an interest rate cut and a hike. By doing this, we investigate if differences in consumption responses to interest rate changes between groups with differing financial vulnerability are symmetric to interest rate cuts and hikes. For many reasons, bank data is scarcely accessible for research, which makes our contribution even more valuable. Extensive data manipulation has been required to prepare the data for analysis.

To conduct the analysis of short-run consumption responses, we employ a difference-in-differences (DiD) research design, assigning treatment to a financially exposed group and comparing them to a financially robust group. Financial exposure is strongly correlated to the life cycle of individuals, which is why we use the lowest and highest loan-to-value (LTV) quantiles by age groups as the control and treatment groups, respectively. We exploit two interest rate changes to estimate consumption response heterogeneity. First, we study the interest rate shock in March 2020, in which the policy rate was lowered by 125 basis points in one week (Figure 4). We then use the interest rate hike starting in late 2021 as a second shock to look for asymmetry in the groups' response to interest rate changes. It is valuable to study whether the consumption response has short-term asymmetric properties, as it can reveal heterogeneity in how the two groups perceive interest rate hikes and cuts. Such results may display important information about relative risk aversion and how risk aversion affects differences in the short-run transmission of monetary policy between different groups.

We focus our analysis on the periods when the policy rate is transmitted to the consumers via a reset of their loan interest rate. In Norway, this typically happens six weeks after the central bank changes its policy rate. During the *interest rate cut period*, we analyze the period of December 2019 through May 2020, in which the pre-treatment period is December through February, and the post-treatment period is March through May. During the *interest rate hike period*, we analyze from September 2021 through March 2022. The pre-treatment period is from September through November, and the post-treatment period is from December through March.

The interest rate shock in 2020 occurred due to the onset of the COVID-19 pandemic, in which aggregate consumption fell dramatically (Figure 3). The results of our analysis indicate that the exposed individuals, in the short run, reduced their consumption by approximately 8 percent less than their robust counterparts, significant at the ten percent level. The interest rate hike happened due to the normalization of the economy going out of the pandemic. During the interest rate hike, we measure no significant differences in consumption development between the two groups. It is infeasible to attribute the results of our analysis solely to the cash flow channel. Compared to calculations on the actual cashflow effects, the results for the interest rate cut period are overestimated. During the interest rate hike period, the calculations imply a negative effect, which we cannot demonstrate.

The robust and exposed groups differ on several key observables. In addition to being less financially robust, the exposed group has a higher share of men and people working in the private sector than the financially robust group. These traits are heavily correlated with risk tolerance, suggesting different responses to shocks. This is the second channel we highlight. We propose that the substitution and the precautionary savings effect work through the risk tolerance heterogeneity channel. The substitution effect describes how differing levels of risk aversion explain different levels of intertemporal substitution in response to interest rate changes. The precautionary savings effect says that there is heterogeneity between how risk-tolerant and intolerant individuals change their marginal propensity to save when met with future uncertainty. Finally, we point out the possibility that the expectations effect of forward guidance affects consumption responses. Druedahl et al. (2022) show that individuals with large liquid assets consider the central bank's forward guidance to a greater extent than their illiquid counterparts, which may also partially explain our results.

In a Norwegian context, research on short-term effects is especially interesting since almost all households have variable-rate mortgages (VRMs) (Statistics Norway, 2023e). Therefore, the short-term effect of interest rate changes ought to be more important than in other comparable countries where a larger share of the debt is in fixed-rate mortgages (FRMs) or adjustable-rate mortgages (ARMs). It is of interest to understand the swiftness with which the interest rate affects the real economy. Therefore, we must understand short-term consumption responses to interest rate changes. Almost all research on this topic in comparable countries uses administrative register data with yearly observations, disabling them from studying shocks in the very short run. The contribution of this thesis is to investigate short-term consumption responses to interest rate changes and to discuss if an approach with bank data is fruitful for these types of analyses.

The structure of the thesis is as follows. Next, we will present some background on the debt situation in Norway and the economic implications of COVID-19. We will then follow with a chapter on theoretical framework and literature, in which we will present key studies for our analysis. Further on, we present the data employed for the analysis, accompanied by descriptive statistics. The subsequent method chapter presents our empirical strategy, with an emphasis on the choice of method and the choice of treatment group and period. Next, the results are presented, followed by a chapter with the closely related robustness checks. The results form a basis for the discussion chapter, in which we draw lines between our results and economic theory.

2 Background

2.1 The Indebtedness in Norway & Macroprudential Regulations

In line with 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 percent, placing Norway as the second highest indebted country of the OECD countries after Denmark (OECD, 2023). The high indebtedness is closely related to the high home ownership rate (Figure 2). As of 2022, households' new installment loans had an average loan-to-value (LTV) ratio of 64 percent and a DTI ratio of 347 percent (Finanstilsynet, 2022a)[1]. In contrast to the prevalence of FRMs and ARMs in Denmark and many other comparable countries, VRMs[2] are predominant in Norway (Statistics Norway, 2023e)[3]. The large share of VRMs gives a rapid pass-through from changes in the central bank's policy rate to the household's interest expenses, making Norwegian households particularly vulnerable to interest rates and income shocks (Gulbrandsen, 2023). These circumstances have raised concerns about financial stability and potential negative consequences should economic conditions worsen. One cause for concern is that households might cut their expenses more than they normally would 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 due to swiftness in pass-through effects.

In order to reduce debt accumulation among at-risk households, macroprudential regulations were gradually introduced in Norway in the wake of the Great Recession. Since the initial introduction in 2011, the regulations have been amended multiple times. As elaborated by the Finansdepartementet (2022)[5], the lending regulation enforces limitations on banks' lending practices and includes several requirements for borrowers. Borrowers are allowed an LTV ratio of a maximum of 85 percent, with required principal payments for loans with an LTV ratio exceeding 60 percent. Second, the DTI ratio cannot exceed 500 percent. Borrowers must also be able to withstand an interest rate stress test of debt-servicing-ability. In force from January 2023, this stress test requires that households are able to manage an interest increase of three percent and a minimum rate of seven percent. The adjustment loosened the previous requirement of withstanding a five percent increase. Additionally, there is a flexibility quota, which is the share of the capital volume of the loans each quarter in which the banks are allowed to deviate from the requirements. From July 2023, the regulations will cover not only mortgages but also loans with other collateral (Finansdepartementet, 2022).

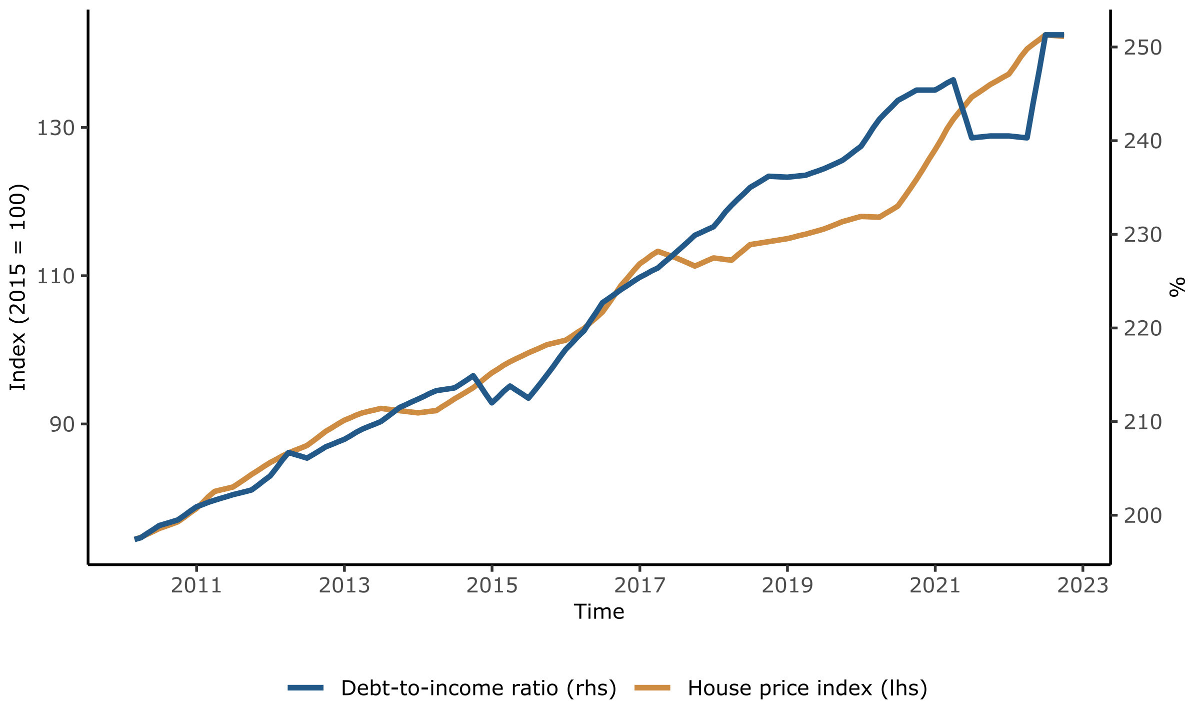
[1] Finanstilsynet is the Financial Supervisory Authority of Norway.

[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.

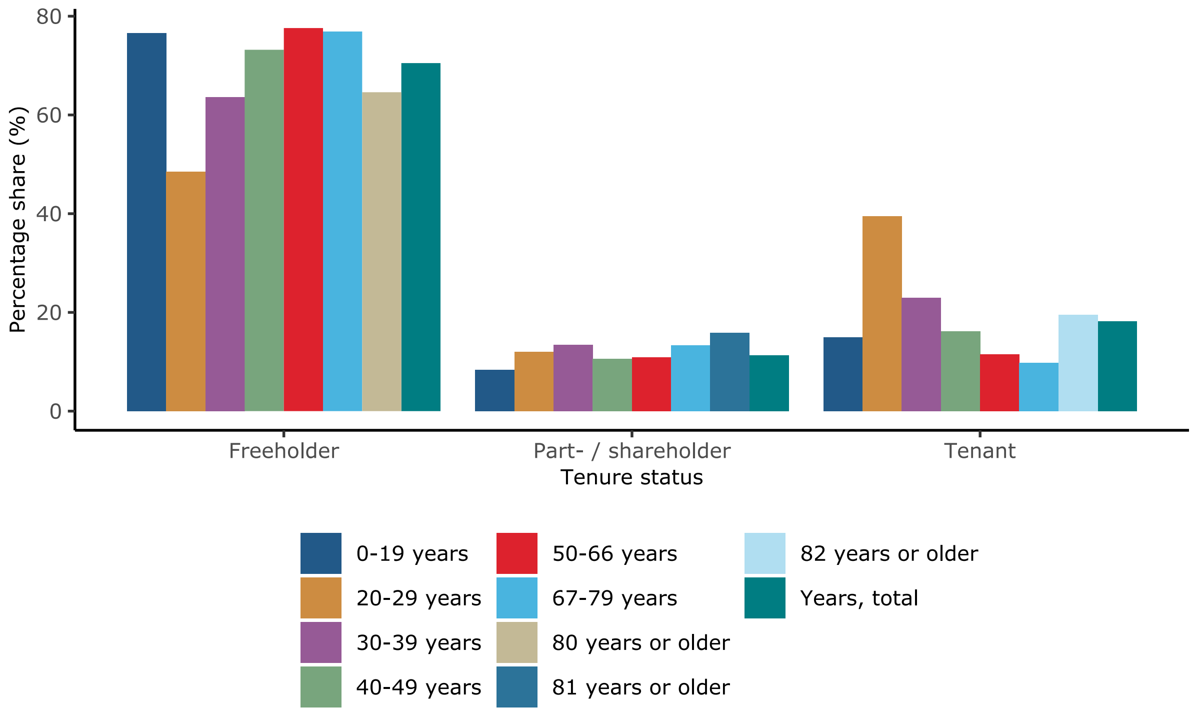
[4] Norges Bank is the central bank of Norway.

[5] Finansdepartementet is the Norwegian Minstry of Finance.



Seasonally adjusted debt-to-income ratio. Retrieved from Statistics Norway (2023d).
Seasonally adjusted price index for existing dwellings. Retrieved from Statistics Norway (2023b).

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



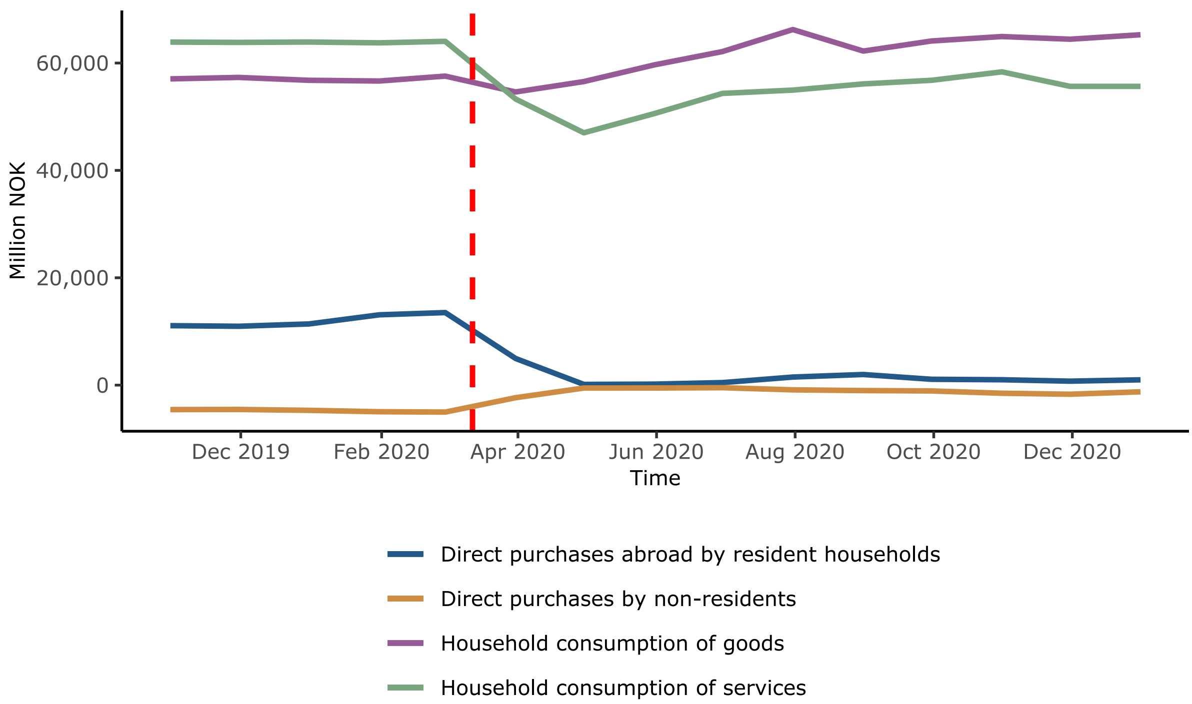
Tenure status for total dwellings in the whole country in 2022. Retrieved from Statistics Norway (2023g).

Figure 2: Home Ownership Rates in Norway

2.2 The COVID-19 Pandemic and Monetary Policy Responses

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

The first period we analyze is the interest rate cut period from December 2019 through May 2020. In response to the pandemic onset, the Norwegian government imposed a national lockdown on March 12th, 2020, to prevent the spread of the virus and protect public health. The lockdown entailed significant economic consequences, characterized by reduced economic activity, increased unemployment, and a cut in interest rates (Koronakommisjonen, 2021). The restrictive infection control measures meant that people had to stay at home, limiting their ability to consume. There was a sharp decline in aggregate household consumption in March and April but with a rapid recovery in spending on goods. As Koronakommisjonen (2022) [6] describes, the measures particularly affected the service industries, which were difficult to operate while maintaining social distancing. Industries related to tourism were also hit hard. From 2019 to 2020, the total household consumption fell by 6.3 percent, particularly driven by the drop in consumption of services. Households shifted their consumption somewhat 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 fall in mainland GDP of 4.7 percent, compared to a counterfactual scenario without a pandemic.



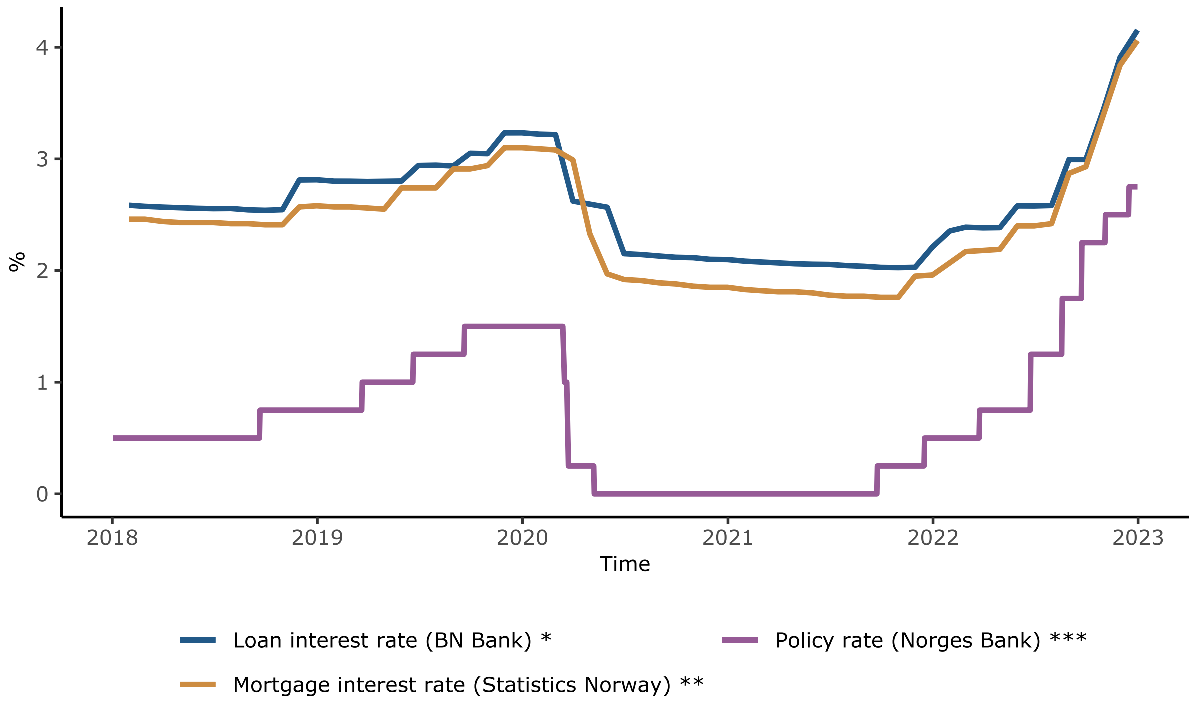
Households' total consumption expenditure. 2020 prices, seasonally adjusted.
Retrieved from Statistics Norway (2023h).

Figure 3: Expenditure Development During the COVID-19 Pandemic

[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.

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

Notably, authorities introduced a series of urgent measures throughout the spring of 2020, which played a crucial role in stabilizing the economy and preventing a more severe recession. Several of these measures affected consumption patterns directly and indirectly. As described in detail by DSS (2022)[8], the measures mainly covered income support for affected workers, grants and loans for businesses, and temporary tax reliefs. Furthermore, layoff regulations were relaxed, and there was imposed temporary flexibility in the mortgage regulations. Additionally, the government introduced stimulus packages.



* 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

[7] Collateral requirements involves the countercyclical capital buffer rate for the banks which was eased from 2.5 percent to 1 percent in March 2020 (Norges Bank, 2022a).
[8] Departementenes sikkerhets- og serviceorganisasjon (DSS) is the Norwegian Government Security and Service Organisation.

The second period we investigate, the interest rate hike period, is the onset of a series of interest rate hikes coming out of the pandemic. This period stretches from September 2021 through March 2022. On September 24, 2021, the Norwegian Government decided that Norway would move to a 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 raised its policy rate from 0 to 0.25 percent. This hike was in line with the forward guidance from the central bank (Norges Bank, 2021a, p. 42; 2021b, p. 48) and thus expected by the market. A further hike of 25 basis points in the policy rate was initiated on December 17. Norges Bank has continued its gradual increases and has reached a policy rate of 3.25 percent as of May 2023 (Norges Bank, 2023). The first transmission of the policy rate to the mortgagors we analyze occurred in December and January when the bank loan interest rate increased by a total of approximately 30 basis points.

The open and unrestricted everyday life was not long-lasting as the new Omicron variant was on its uprising, marking the interest rate hike period. On November 30, the government reintroduced infection control measures to limit the spreading of the Omicron variant. In particular, economic activity in the run-up to Christmas was struck. Additionally, in early 2022 a different set of events led to economic uncertainty, as the Russo-Ukrainian war became more and more of a threat, culminating with the Russian invasion on February 24, 2022. Since Russia is a prominent exporter of oil and gas and because Ukraine and Russia combined contribute roughly 30 percent of the world's wheat export (Norges Bank, 2022c, p. 16), commodity prices increased sharply. The war led to fear of inflation and high levels of uncertainty. Comparing Monetary Policy Reports from Norges Bank during this period, we see that the Norges Bank's forward guidance was adjusted upwards in the wake of these events due to the emerging inflation.

Overall, during both the interest rate cut and hike period, there were lots of significant macroeconomic news apart from the interest rate changes. These events contributed to the monetary policy actions carried out. As such, other factors contribute to fluctuations in private consumption besides the interest rate fluctuations we focus on in the thesis.

3 Theoretical framework and literature review

In this chapter, we delve into the framework of private consumption in macroeconomics. We will explain how the central bank affects consumption by conducting monetary policy. Furthermore, we will highlight the traditional life-cycle hypothesis. Next, we will present a standard two-period macroeconomic model of consumption and describe how the interest rate affects consumption in this model. Further, we will emphasize the importance of considering individual heterogeneity in risk tolerance when analyzing consumption responses. We will also review previous research, focusing on the papers most relevant to ours.

3.1 Transmission Channels in Monetary Policy

Private consumption comprises roughly half of mainland Norway's gross domestic product (Statistics Norway, 2023h). As such, it serves as a significant channel through which monetary policy influences the economy. Therefore, private consumption is a critical factor that Norges Bank considers when conduct monetary policy.

Norges Bank's monetary policy framework is flexible inflation targeting. Its main objective is to maintain price stability, with additional considerations of keeping a high and stable output and employment and mitigating the build-up of financial imbalances (Norges Bank, 2021d). Norges Bank's primary instrument is the policy rate, which affects the market rates and banks' deposit and lending rates.

According to Norges Bank (2022d), the primary transmission channels of the policy rate to the real economy are the demand channel, the exchange rate channel to inflation, and the expectations channel. The demand channel is further divided into the interest rate channel to total demand, the wealth channel to consumption, the cash flow channel to total consumption, and the exchange rate channel to total demand. Through these transmission mechanisms, the central bank stimulates or dampens economic activity.

Both the cash flow channel and the interest rate channel affect total demand. The cash flow channel is a direct income effect from changes in interest expenses due to changes in the interest rate. An interest rate cut increases disposable income for individuals with net debt, which is the case for the average Norwegian individual (Norges Bank, 2022d). The interest rate channel to total demand works by influencing consumption and investment through policy rate changes. The channel is based on the principle of intertemporal substitution described later in this chapter and affects individuals' incentives for borrowing and spending.

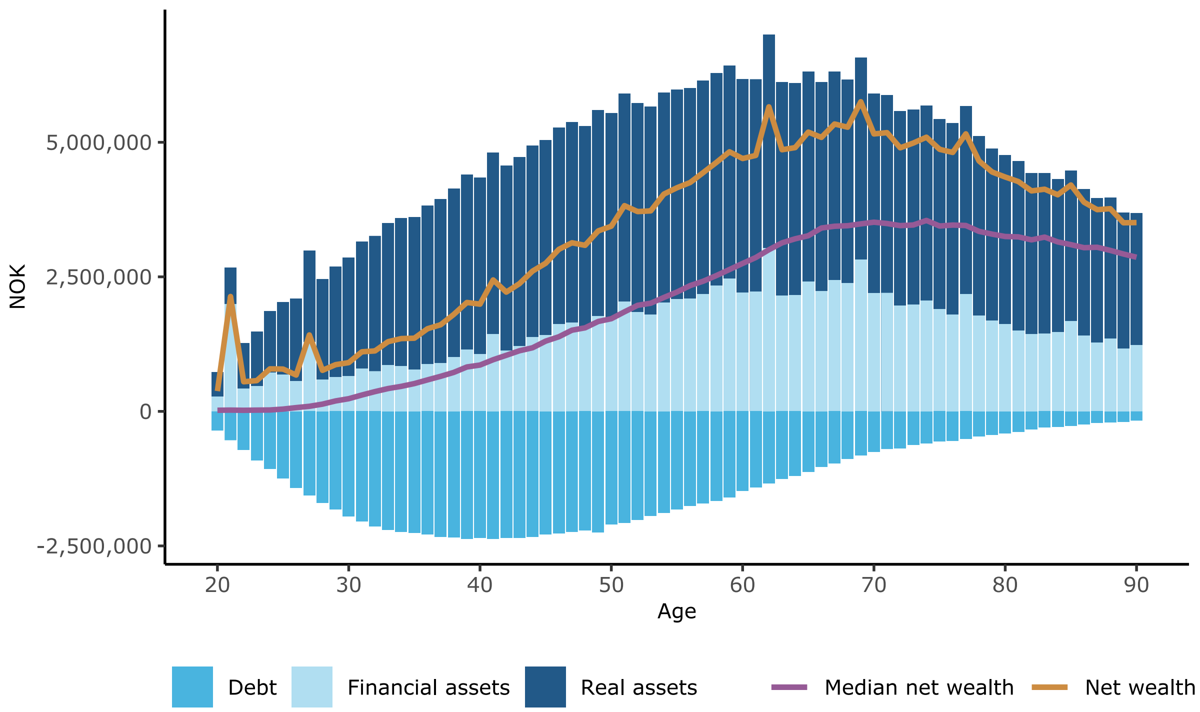
The central bank also affects consumption through the expectation channel. The central bank does this using forward guidance, in which they forecast their future anticipation of the policy rate. Norges Bank relies on the Norwegian Economy Model (NEMO) to produce forward guidance. NEMO is a macroeconomic model used for forecasting and monetary policy analysis. One of the central equations NEMO relies on is the Euler equation (Brubakk & Sveen, 2009), which will be discussed in the two-period consumption model.

This thesis does not emphasize the exchange rate and wealth channels to consumption. Krugman et al. (2018, p. 434) state that prices are relatively rigid in the short-run. There is a lag before the exchange rate's effect on net exports and imported inflation, mainly since exporters and importers sign long-term contracts. These factors indicate that we do not have any reason to believe that the exchange rate channel affects different groups heterogeneously in the short-run, which is why we do not emphasize it in this thesis. Lastly, the wealth channel, which primarily works through the effect of the policy rate on housing prices (Norges Bank, 2022d), is unlikely to be materialized in the short-run due to sluggishness in transmission from monetary policy.

3.2 Macroeconomic Framework

In this section, we will examine the life-cycle hypothesis and its implications on consumption patterns among individuals. Afterward, we will present its limitations and shortcomings, focusing on the inability to explain the magnitude of consumption response. Then, we turn our focus to a two-period consumption model, in which a discount factor, interest rate, and risk aversion enter the model. Finally, we will explain the nature of the heavily intertwined buffer-stock and precautionary savings theory.

First, we examine the life cycle and permanent income hypotheses proposed by Ando and Modigliani (1963) and Friedman (1957), respectively. These models are very similar and provide an essential foundation for understanding consumption patterns among individuals. Both theories state that individuals seek to distribute their consumption optimally throughout their lifetime. Individuals find it optimal to sustain a constant consumption level over time, a phenomenon known as consumption smoothing. The smoothing is achieved by allocating loans, savings, and investments in line with income fluctuation and age. In earlier stages of life, when individuals typically have a lower income level, they tend to borrow to finance spending and investment, typically in education and housing. As they approach retirement age, they tend to have repaid debt and accumulated assets and will rely on saved funds and pension benefits to finance consumption through retirement. Both models are based on complete information about future incomes and preferences. Empirical studies estimate that the life-cycle hypothesis fails to explain the magnitude of consumption response to income shocks (Jappelli & Pistaferri, 2010; Pemberton, 1997). It is clear from Figure 5, based on Statistics Norway data, that the life cycle hypothesis partially explains wealth and debt patterns among different age groups and is valid to a certain extent.



The figure shows the 2020 composition of mean wealth by age in Norway, retrieved from Statistics Norway (2022). The bars are composed of positive values for real and financial assets and negative values for debt.

Figure 5: Age-Distributed Debt and Wealth[9]

Equations 1 through 4 provide the mathematical foundation for the model for individuals' consumption decisions and is based on Romer (2019, pp. 386-387), in which risk aversion, interest rates, and discount factor enter the model.

$$u'(C_1) = E_1(u'[C_2]) \tag{1}$$

$$U = \Sigma_{t=0}^{1} \frac{1}{(1+\rho)^t} \frac{C_t^{1-\theta}}{1-\theta} \tag{2}$$

$$\frac{1}{(1+\rho)^1} C_1^{-\theta} = (1+r) \frac{1}{(1+\rho)^2} C_2^{-\theta} \tag{3}$$

$$\frac{C_2}{C_1} = \left(\frac{1+r}{1+\rho}\right)^{\frac{1}{\theta}} \tag{4}$$

For simplicity, we consider a two-period model in which one must consume either today or tomorrow; Equation 1 is an Euler-type equation solving the optimization problem of choosing how much to consume today and how much to consume tomorrow. For the individual to be utility-maximizing, the equation states that the marginal utility, u' of the consumption in period one, C_1 equals the expected present marginal utility from consumption in period two $\left(E_1(u'[C_2])\right)$.

An individual's total utility is given by Equation 2. Total utility in the two periods, *U,* is given by the sum of the present consumption values in both periods discounted by the individual discount rate, ρ, and the individual level of risk aversion, θ. The utility is unique for each individual in that the ρ and θ vary between individuals. A high discount factor, ρ,

[9] Key findings of figure: Wealth increases with age until the late 60s, followed by a modest decrease. Debt also increases with age, peaking in the age span 37-44 years, before declining (Statistics Norway, 2022).

means that the individual does not value future consumption very highly compared to present consumption. The individual is impatient. The risk aversion, θ, is given by the inverse of the relative elasticity of substitution between consumption in the two periods. If θ is approaching 0, the elasticity of intertemporal substitution for the individual is approaching infinity, and 1, if θ, it is approaching 0.

In Equation 3, we have set up the first-order condition from Equation 1 with utility functions as in Equation 2, but with a non-zero interest rate. The left and right-hand side of the equal sign is given by marginal utility in period 1 and 2, respectively. These must be equal to maximize individual utility.

Equation 4 shows the ratio of consumption in periods 1 and 2 and is a function of the rate of interest, the individual discount rate, and individual risk aversion. One can see that given constant levels of risk aversion and discount rate, an increase in the interest rate will shift consumption towards period 2, as is intuitive due to changes in opportunity cost from postponing consumption to the second period.

In this model, the only direct transmission mechanism of the interest rate onto the individuals' consumption decisions is that higher interest rates affect the intertemporal substitution. Flodén et al. (2021) point out that several studies have shown that empirical models based on this macroeconomic approach fall short when explaining the magnitude of interest rate shocks on private consumption by neglecting role of the cash flow channel.

To extend our understanding of the macroeconomic framework, we explore the buffer-stock theory introduced by Carroll (1997); (Carroll & Samwick, 1997) which adds dimensions of prudence and impatience to the life-cycle hypothesis. The theories are concerned with how individuals maintain a certain buffer level of precautionary savings to cope with uncertainty about future income and expenses. Individuals have a precautionary savings motive, in which they save a portion of their income to create a buffer stock of wealth that they can use to smooth consumption in case of income shocks (Carroll, 1997; Carroll & Samwick, 1997). Additionally, Carroll (1997) argues that individuals are impatient in the sense that if they had had perfect information about future incomes, they would consume more in the present period. Such a response could be due to them expecting large future income growth or a strong preference to consume more today (Carroll, 1997). The Buffer Stock theory argues that individuals have a personal savings level that is their target. If they are below this target, individuals will have a higher marginal propensity to save from transitory positive income shocks to increase precautionary savings. If they exceed their target, they will decrease the marginal propensity to save as impatience dominates prudency. Carroll (1997) produces results that show that given sufficiently impatient individuals, consumption growth, on average, equals labor income growth.

3.3 The Cash Flow Channel of Interest Rate Changes

Next, we investigate the cash flow channel, which according to several papers, serves as a significant channel for monetary policy transmission. According to traditional macroeconomic policy, the only effect on consumption from interest rate changes is the substitution effect through intertemporal substitution. The effect will only be as large as the new interest rate changes the equilibrium of the Euler equation optimization problem.

Flodén et al. (2021) argue that there may be other channels through which the interest rate affects consumption apart from intertemporal substitution. As mentioned, the cash flow channel is the channel through which consumption the interest rates work on 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 mortgagors have VRMs, the cash flow channel should go rapidly into effect as it hits mortgagors shortly after the central bank changes its policy rate. In the context of our dataset, the cash flow channel suggests that the financially exposed group should change their consumption more relative to the financially robust group when faced with loan interest rate changes. This is due to differences in indebtedness, which means that the disposable income shock will be greater for the exposed group when the interest rate changes. According to Flodén et al. (2021), the cash flow channel need not be significant. Given perfect information on future interest rate levels and income, perfect access to capital markets, and a sufficient buffer stock level, individuals will seek to smooth income shocks from interest rate changes and, hence, will not necessarily change their consumption.

In a situation in which 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 suggests, meaning the cash flow effect will be significant.

3.4 Heterogeneity in Individual's Risk Tolerance

Delving into individual heterogeneity, we examine how individuals' risk perception influences their choice of economic exposure and how they respond to interest rate changes. 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.

By presenting hypothetical gambles to respondents over ten years, Sahm (2012) gathers data and provides insights into individuals' risk preferences. Sahm shows how risk tolerance decreases with age. This pattern is also prominent in finance, in which she shows that young people are significantly more willing to invest in riskier assets. Further on, Sahm finds that having major health issues or becoming unemployed results in lower risk tolerance. She also substantiates the link between lifetime income and risk aversion, in which a higher income is associated with a higher risk tolerance. However, she finds no significant effect of wealth on risk tolerance. Her findings also suggest that individuals with greater indebtedness have higher risk tolerance and that more risk-tolerant individuals choose riskier careers. Sahm (2012) underlines the positive relationship between the business cycle and risk-taking, which is undeniable. Economic upturns increase risk-taking among individuals. Since the risk profile of individuals is related to how precautionary they are, the findings of Sahm are relevant for the buffer-stock behavior.

Further 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, in which they find that individuals with high-risk tolerance more often choose occupations with high earnings risk, which predominantly exist in the private sector.

3.5 Previous Research on the Cash flow channel

Several earlier studies have researched the cash flow channel of the interest rate using microdata. Studies like Di Maggio et al. (2017), Flodén et al. (2021), and Holm et al. (2021) reveal that individuals with lower levels of liquid assets and higher levels of debt tend to respond stronger to interest rate changes. However, few studies have been done on Norwegian data in which the prevalence of VRMs is very high (Statistics Norway, 2023e). Further on, papers focusing on short-term shocks are scarce.

Di Maggio et al. (2017) study the interest rate pass-through on individual-level data from a private US company with data access to 90 percent of the privately securitized mortgages from the period they study. They estimate the cash flow channel by studying how decreased mortgage payments affected durable consumption among households that held five-year fixed ARMs granted between 2005 and 2007. These ARMs had their interest rate reset between 2010 and 2012. Due to the interest rate cuts during the Great Recession, these loans were reset to a much lower interest rate, causing an upward shift in disposable income for the mortgagors. Di Maggio et al. compare these mortgagors with ones that held ten-year fixed ARMs meaning they did not have their interest rate renegotiated until much later. They find support for the cash flow channel on durable consumption, measured in the change in consumption of cars. Further, they show that a higher level of voluntary deleveraging weakens this effect. They also show significant heterogeneity in the cash flow channel, with more liquid households having a lower MPC towards new cars. Instead, these individuals spend more of their increased disposable income on voluntary deleveraging compared to households with lower levels of liquid assets.

Flodén et al. (2021) estimate the cash flow channel using Swedish administrative registry data. They find a significant cash flow channel when comparing debt holders and non-debt individuals. Namely, they find that debt holders decreased their spending by 0.23 to 0.55 percentage points more than non-debt individuals in response to a one percentage point hike in the interest rate. They also find significant differences in the consumption response to interest changes between ARM– and FRM holders. Additionally, they find that those with low levels of liquid assets respond stronger than those with high levels. When they look into heterogeneous effects, they find that those who respond the strongest to interest rate changes are the households with the lowest level of liquid assets, the highest level of DTI, and the highest share of ARMs.

Gerdrup and Torstensen (2018) & Holm et al. (2021) estimate the cash flow channel using Norwegian data. Gerdrup and Torstensen (2018) perform a static analysis and find that the cash flow channel has become more relevant in recent years due to rapid growth in debt levels compared to income growth and the development of liquid assets. They find 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 what would be expected given the debt development. This is because households possess greater liquid funds than they used to. Holm et al. (2021) estimate the cash flow channel using the method from Romer and Romer (2004) to estimate exogenous interest rate shocks. They perform a similar study as Flodén et al. (2021) but on Norwegian data instead of Swedish. They find a significant cash flow channel and identify that households with different levels of liquid funds have different MPCs. Their results point in the same direction as Fagereng et al. (2021), who find that the MPC among lottery winners is larger among households with low levels of liquid funds.

One last notable contribution is a study by Druedahl et al. (2022). They study the forward-looking behavior of households and anticipation effects on consumption. The researchers employ a combination of Danish bank data and administrative tax data to study borrowers with 1-year ARMs. A sample of households from the bank receives a letter containing information on an expected change in mortgage payments six months ahead. The findings of Druedahl et al. (2022) suggest that households unlikely to have liquidity constraints increase their consumption when informed about the interest rate change but not when the actual cash flow effect hits. On the other hand, households that are likely to be liquidity-constrained increase their consumption when the cash flow effect hits and not when they are notified about the future interest rate change.

4 Data

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

4.1 Data description

The data employed for the analysis is a panel of mortgagers in BN Bank, a nationwide commercial bank. The bank is an internet-only bank with a total retail lending of about 30 billion NOK and a current customer basis of 101,000 personal customers, of which 15,000 have mortgages (BN Bank ASA, 2023). The bank's customer portfolio is spread throughout Norway but is predominately based in South-Eastern Norway (Figure 7). Having been granted access to internal administrative data from the core system of BN Bank gives us the opportunity to delve into a novel dataset with excellent research potential.

Initially, the panel spans from 2010 until 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[10], and previously unsecured consumer credit[11]. The process from raw data to a dataset adapted for our purposes has required extensive data manipulation. According to strict privacy considerations in a bank, each customer is pseudonymized.

Table 1 shows descriptive statistics for the entire sample during the two periods of interest. Here, we will comment on the most important differences between the two sampling periods. The difference in mean consumption between the two periods is significant, with a mean of 14,500 NOK and 16,400 NOK in the cut and hike periods, respectively. As discussed in Chapter 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 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 during the interest rate cut period. Partially, this is because the period is one more month longer, but likely 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 have high levels of deposits. However, this is speculative, and we do not know for sure.

[10] 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.

[11] 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

The data employed for the analysis is filtered extensively based on reasonable requirements. According to a survey by Forbrukerrådet (2023, p. 33),[12] more than half of Norwegians have more than one banking relationship. Hence, we strive to restrict the dataset to include only customers that use the bank actively for spending, preferably as their primary banking relationship. As a relatively small bank with a narrow focus, BN Bank does not offer savings products apart from high-interest rate accounts. The fact that the bank does not provide products such as mutual fund savings means that those who wish to make further investments will have to do so elsewhere. Consequently, a share of the customers of BN Bank has placed funds in other banks that are unobserved to us.

Since we do not possess knowledge of the customer's activity in other banks, we set some requirements to omit customers unlikely to use BN Bank as their daily spending bank. We filter out observations with an average monthly spending of less than 5,000 NOK and fewer than five monthly card transactions. It should be noted that it is not feasible to identify the desired individuals with complete accuracy, and this omission naturally limits the sample size.

Furthermore, we perform additional filtration steps. We omit customers with serial loans since the meager share of customers having such loans will likely have different traits and behavioral patterns than standard, annuity customers. Also, we require that customers are observed at least once during the pre– and post-treatment period. Doing this prevents disturbance from newly entered or terminated banking relationships. Additionally, since the *Debt Expander* control variable is dependent on the relative change between the periods, two periods are necessary to define it. We omit extreme values in consumption by setting a lower and upper fence. We define the lower limit by subtracting 1.5 of the interquartile range from the first quartile. The upper limit is defined by adding 1.5 of the interquartile range to the third quartile.

Some individuals in the panel are observed with very large loans related to their business activities. Typically, these customers are self-employed. To avoid the activity from non-private behavior distorting the results, we omit individuals with a loan size greater than 10 million NOK, corresponding to the 99^{th} percentile.

Further on, to overcome issues due to the 2020 regional reform, current names of counties and municipalities are used throughout the whole period. By considering the postal location, which was mainly unaffected by the regional reform, we can distinguish between those whose residing municipality or county changed its name and those who moved. Such residential data forms the basis for defining whether customers live in a large urban area, an important control variable in the analysis. Since the interest rate cut period is simultaneous to when most regional changes were implemented, not correcting for this could have implications.

4.3 The Consumption Measure

Our key variable of interest, consumption, captures debit card transactions, cash withdrawals, and VIPPS[13] transactions. As the consumption variable is an aggregate measure, we cannot observe the granularity in individuals' consumption. A common approach in the field of literature is to distinguish between the consumption of goods and

[12] Forbrukerrådet is the Consumer Council of Norway.

[13] VIPPS is a mobile payment application with a market dominating position in Norway.

services and the consumption of durables and non-durables. The consumption measure fails to make these distinctions, entailing some implications. As previously discussed, the COVID-19 measures taken by the authorities were much more pronounced for the spending on services than goods (Figure 3). The consequences of this are discussed in Chapter 2.2.

Further on, Black and Cusbert (2010) suggest that the consumption of durables is closer correlated to the economic cycle than of non-durables, as one can often postpone purchasing these goods during challenging economic times. They characterize durable goods, such as vehicles and major appliances, by providing a utility stream over time, while non-durable goods are typically consumed immediately. Nor will the consumption variable capture a significant part of the consumption of durable goods since people often purchase these through wire transfers rather than card payments.

A common approach in other studies is to use register data with complete information. Registry data allows clustering the individuals to the household level and observing household consumption, in which case, it does not matter whose name is on the mortgage. In addition, studies done on data with complete information have the advantage of allowing scholars to use an accounting identity to obtain a full overview of consumption. When using register data, one can observe the full balance sheet of the individual, and hence there will not be any error in the consumption measure. Access to register data also allows researchers to calculate a more precise MPC since they will have a complete overview of households' income.

4.4 Representativeness of sample

In this section, we will discuss the sample's representativeness, which differs from the general Norwegian population in some respects. Since we are analyzing mortgagors, certain age groups are overrepresented. The age distribution of our sample differs from the general population. The age distribution of the BN Bank customer portfolio is more centered around the middle-aged population. Observing this age distribution is natural as people typically take on their first loans in an establishing phase of life and amortize them as they age. Further, the sample is skewed in favor of men. The gender gap in the sample may have several explanations, but men are predominately the main borrower in relationships. This pattern is also prevalent in other banks (Lycke, 2020). Hence, our sample is assumable representative of the general mortgagor.

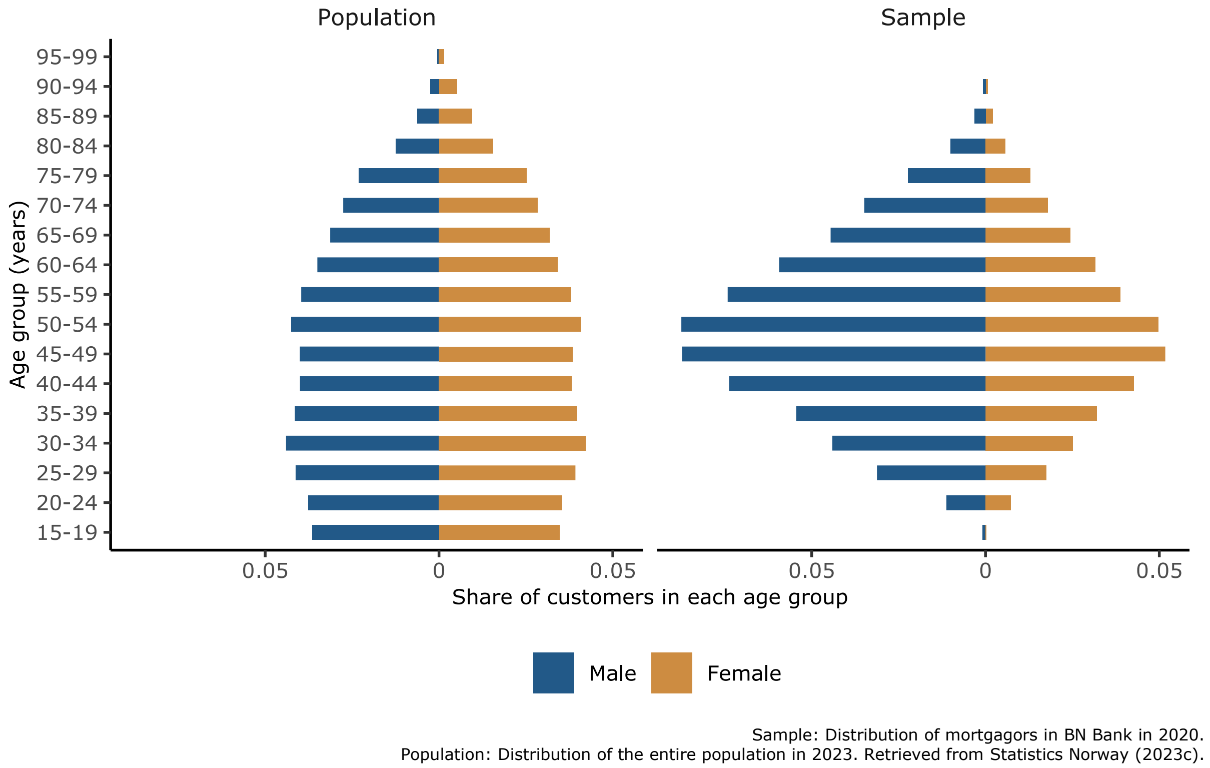


Figure 6: Population Pyramid

BN Bank is a nationwide bank, but there is an overweight of customers in South-Eastern Norway (Figure 7) and customers living in large urban areas (Table 2). Since individuals choose which 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, their prices, their marketing, and their strategy. As BN Bank is an internet-only bank, individuals from the whole country do have access to the bank, but South-Eastern Norway is a target area for the bank.

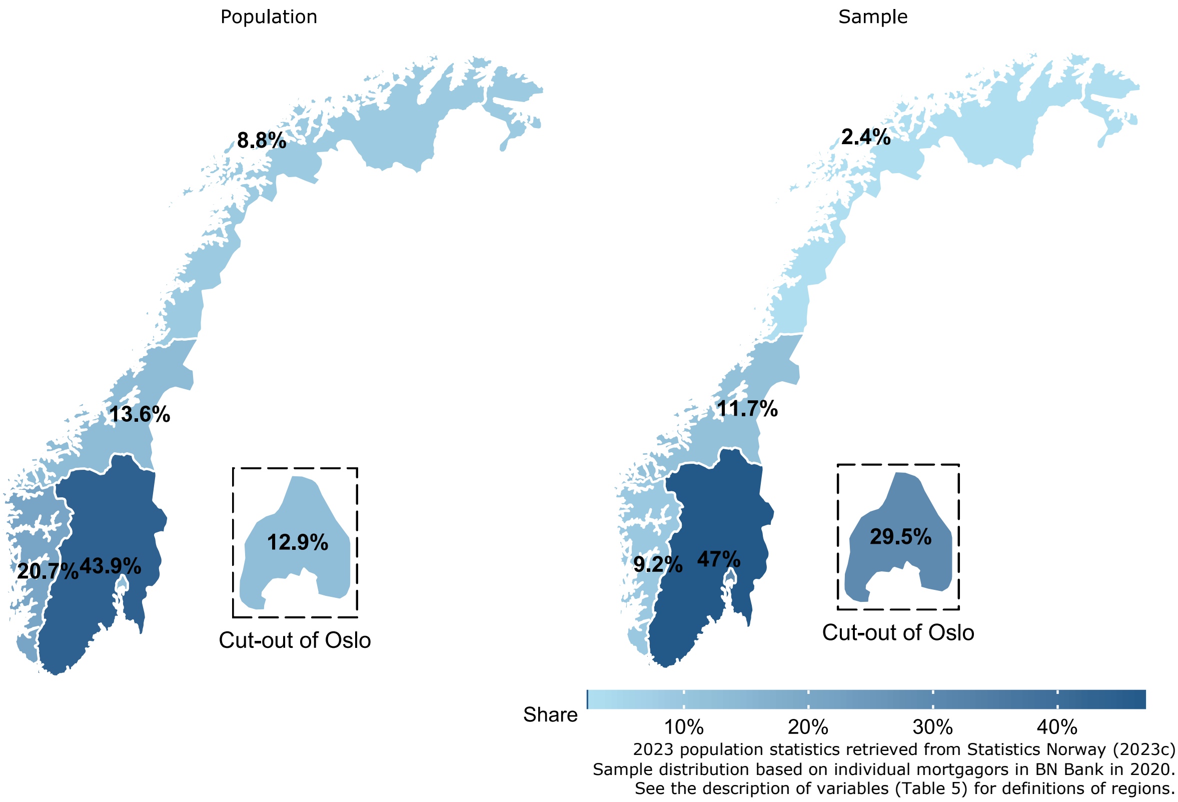


Figure 7: Regional Distribution

4.5 Control Variables

A series of control variables are included in the analysis. This section will explain the control variables and describe how they are defined. We discuss the rationale for introducing each control in Chapter 5.6. Further details on the variables are provided in the variable description (Table 5).

Firstly, we control for some demographic variables, including gender and retirement status. Since we do not directly observe which customers are retired, we define them as *Retired* if they are older than 67. Additionally, we create the dummy *Large Urban Area*, stating whether an individual resides in an urban settlement with more than 100,000 inhabitants. These areas involve the largest cities and surrounding municipalities where the settlement is considered contiguous[14] (Statistics Norway, 2023a).

Furthermore, several loan-specific controls are included. We define the dummy *Large Buffer* based on customers' deposit holdings, which include checking and savings accounts. It comprises individuals with deposits larger than 200,000 NOK, corresponding to about the highest quintile. Furthermore, we define a dummy for individuals that expand their debt from the pre-treatment to the post-treatment period. By looking at the relative change in average debt between the two periods, we characterize an individual as a *Debt Expander* if their debt increases by more than one percent. This increase in borrowing could be through either mortgages, home equity loans, or equity release mortgages.

Moreover, we define the dummy variable, *Co-dependent,* indicating whether the individual has a co-borrower on their mortgage. 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

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

borrowers is set up such that the loan is registered under the main borrower's account. As a result, co-borrowers do not have the loan registered in their account, excluding them from our dataset. It is not possible to link the main- and the co-borrowers, preventing us from clustering individuals together on the household level. It should be noted that we do not identify customers who have a co-signer on their mortgage. The co-signers provide collateral and are obliged to repay the loan but are not co-owners of the property. Typically, co-signers are parents helping their children purchase their first home.

The dataset also contains data from loan applications. Here, most of the more detailed information about household structure is gathered. For instance, we can observe income, family structure, and other important measurements. Furthermore, this data is seldom retrieved as it is only collected in connection with alterations to existing loans or applications for new loans. Consequently, the accuracy of the variables gathered from loan applications is questionable, and we will not employ it during the analysis.

5 Method

In this chapter, we will discuss the empirical strategy of a DiD approach, followed by the choice of the treatment groups and the timing of treatment. Additionally, we will discuss heterogeneity between the groups. Lastly, we will present our model and model specifications.

5.1 Empirical Strategy

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

We simplify our dataset to a setup with two periods and two groups. This setup enables us to use time-invariant control variables, which most of our controls are, and to measure average treatment effects on 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 measure general responses on the group level between the financially exposed and robust.

Individual level fixed effects models would have had trouble isolating individuals' responses to interest rate changes through consumption from other economic effects. One such effect is seasonal variations, which are so large that they outweigh any effect we estimate. Also, given the size of the panel and the emphasis on short-term effects in this thesis, we would run into problems 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 the loan size, the number of periods until default and other indicators such as having freedom of installments. The effect in relative terms depends on the LTV ratio and the DTI ratio. The DTI ratio in our dataset is mostly based on outdated observations and is not a reliable measure. Hence, we use the LTV ratio as a relative measure instead. A relative measure of indebtedness is preferred as a measure of financial robustness. This is because individuals with higher income and wealth levels will often have larger loans. However, this does not necessarily mean they are more financially exposed since they have higher incomes and wealth.

5.2 Choice of Treatment Group

There are several endogeneity challenges with the traditional measurements of financial exposure. The size of the loan and the LTV ratio especially are heavily correlated with the life cycle of an individual, as seen in Figure 5. Customers who recently entered a loan agreement naturally have a high LTV ratio. As young people dominate the group of new mortgagors, 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 typically have amortized their loans for many years (Statistics Norway, 2023d). This pattern implies that younger individuals should respond more strongly to interest rate changes. Furthermore, the fact that the average LTV ratio has increased drastically in the last decade amplifies this effect further, as discussed in Chapter 2.1.

To evaluate the robustness of individuals while controlling for life-cycle heterogeneity between age groups, we use a measurement of the LTV level compared to the individual's age group. We assign those between the 80th to the 98th percentile of LTV level for their age group as the treated group. They will be relatively exposed to interest rate changes. We label those in the 2nd to 20th percentile as the control group since they are relatively unexposed to interest rate changes. This approach implies that the control group is also treated to a certain extent. However, the treatment difference is significant since the exposed group, on average, is more than twice as indebted (Table 2). The selection leaves 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 distribution and age distribution of the financially robust and exposed group are visible in Figure 8. The approach of using the age-adjusted measure greatly balances the age distributions, although they do not match perfectly. Since we use quantiles to construct the financially exposed and robust, it is natural that the LTV distributions overlap slightly around an LTV of 0.5. If an older person has an LTV of 0.5, they are much more likely to be exposed than a younger person with an LTV of 0.5. Since the treatment classification is based on age groups, the level of LTV among the financially exposed and robust are different in different age groups. This factor creates the highly uneven LTV distribution in Figure 8.

We omit all individuals between the 20th and 80th percentile of relative LTV and those below the 2nd and above the 98th percentile. By doing this, we isolate the exposed and robust individuals. Omitting those between the 20th and 80th percentile will ensure that the difference between the two groups is significant enough to ensure a sizable difference in treatment magnitude between the treatment and control groups. By excluding the far ends of the LTV distribution, we omit outliers.

Another reason for using a relative LTV measure relative to age measurement 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 getting infected was generally strongly correlated with age. As this likely caused different age groups to curb consumption differently, we avoid this issue by age-adjusting our treatment measure.

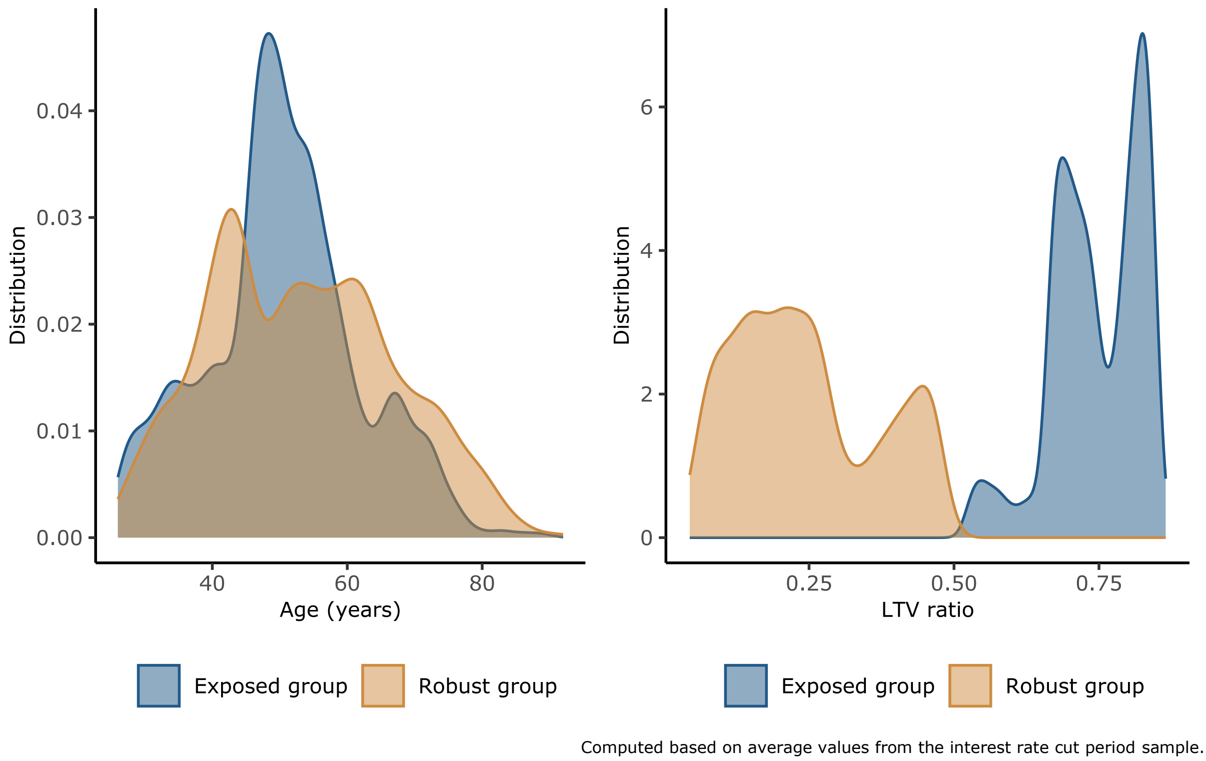


Figure 8: Age and Loan-to-Value Ratio Distribution

5.3 Timing of Treatment

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

The first period we analyze, which we will refer to as the interest rate cut period, is from December 2019 until May 2020. After the initial shock of the COVID-19 pandemic in March 2020, 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 the policy rate changes to the banks adjusting their loan interest rate to the consumers. However, there was a deviation from this practice due to the special situation surrounding the COVID-19 pandemic. To some extent, the interest rate cut benefited mortgagors at once. Specifically for our sample, as seen in Figure 4, the March cuts in the policy rate were partly passed through to the mortgagors' loan interest rate immediately, while the remaining was transferred in June. To capture the effect of one interest rate shock, we define the post-treatment period as March through May 2020. The pre-treatment (comparison) period is defined as the beginning of December 2019 to the end of February 2020. To avoid capturing the subsequent loan interest rate cut in June, we only consider the period up to May. By choosing such a short time period, we aim to evaluate the immediate short-term consumption response and not the medium/long-term effect. By considering Figure 9 we observe that the treatment groups have fairly parallel trends.

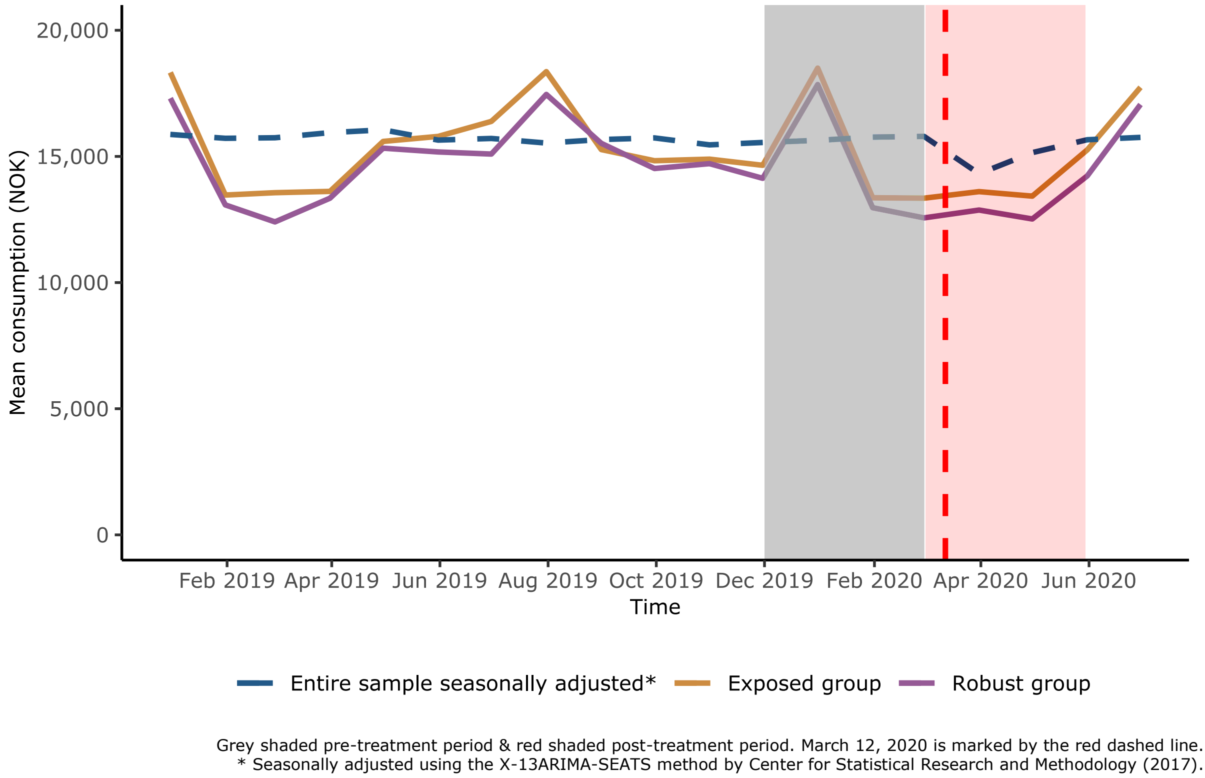


Figure 9: Consumption Trends - Cut Period

The interest rate hike period is defined from September 2021 until March 2022. We evaluate the time period when the first interest rate hikes were transferred to the sample. The first policy rate hike came from Norges Bank in September 2021 and was passed through to the mortgagors' loan interest rates in December and January (Figure 4). Using the same arguments as with the interest rate cut period, we seek to avoid estimating the effect of subsequent series of interest rate increases. Consequently, we time the treatment as starting in December 2021 and lasting until March 2022. By observing the individuals a couple of months after the full treatment has occurred, the interest rate changes have had time to materialize in consumption.

Figure 10: Consumption Trends - Hike Period

5.4 Heterogeneity Between Control and Treatment Group

In addition to a high LTV level, the individuals in the exposed group differ from the robust group in other characteristics. The heterogeneity is visible in Table 2. In general, exposed individuals possess less liquid funds and have larger loans. There is also a higher share of males in this group and a higher share working in the private sector. Furthermore, there is a lower share residing in large urban areas. This is problematic for the first part of our analysis, in which the COVID-19 restrictions play a big part in individuals' ability to consume. However, the age distribution between the treatment and control groups is relatively homogenous, which tells us that we circumvented the problem of a high correlation between age and LTV.

The fact that the exposed individuals have higher loans and possess smaller liquid funds favors this analysis, as these traits strengthen the assumption that these individuals are less financially robust than the "robust" group of individuals. These results allow us to label these groups as financially robust and exposed with greater certainty. We do not demand further criteria to be considered part of the treatment group as this would lead to fewer observations and hence a significant loss in degrees of freedom. Limiting degrees of freedom harms the precision of the analysis. The latter is a concern since the size of our dataset is not as large as the datasets used in earlier studies. Another concern with basing treatment on other financial variables, such as deposits, is that it is likely that the observations are deficient because we cannot observe individuals' full balance sheets.

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

The above leads us to present our main model as Equation 5:

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

In Equation 5, subscript i represents the robust and exposed group, respectively. The subscript *post* states whether the variable indicates the *post* interest change period. The model is equivalent both for the interest rate hike and the cut period. 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 the post-period 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, there is a significant difference in the consumption development between the robust and exposed groups between the pre and the post-period.

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

5.6 Model Specifications

We employ several tactics to add control for heterogeneity between the control and treatment groups on characteristics that we suspect are correlated with consumption but not with financial exposure. By including control variables, we limit the concern of omitted variable bias. Thus, we aim to isolate the interest rate effect. First, we run the model with a set of observable covariates that we believe are influential. Additionally, there is a concern regarding heterogeneous responses to the surrounding economic situation, adding bias to the estimated effect. We limit this concern using interaction controls.

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

Model one is the baseline DiD model without any additional explanatory variables. We estimate this model to capture baseline differences between the exposed and the robust group. In model two, we add control variables for being co-dependent, for gender, and for being retired. During the interest rate cut period, we also add a control variable for the unemployment level in the given month. The *co-dependent* covariate is added to control for any systematic differences in the consumption level between those solely responsible for their loan and those with a co-borrower. It is reasonable to assume that those who share the household expenditures with a second person have a different consumption pattern. For instance, one part may handle the mortgage expenses, while the other pays for other commodities. From our dataset, it is apparent that those who are co-dependent consume less than those who are not. The co-dependency covariate helps us control bias originating from the fact that there are slightly more individuals in the financially exposed group with a co-borrower. The *gender* control variable is introduced due to different consumption patterns between genders and because the exposed group has a larger share of men than the robust group. Also, our data shows that men consume slightly less than women do.

Additionally, we include a control for retirement, as we expect retirees to have a different consumption pattern compared to the rest of the population. This is partly due to the lack of holiday pay but also the fact that they might respond differently to macroeconomic shocks. During the COVID-19 pandemic it is even more likely that the consumption patterns differ, as older people were particularly vulnerable in case of infection. Heterogeneity in fear levels and risk perception likely affected their consumption response. Also, our dataset shows that retirees consume less than the rest of the sample. As the share of retirees is twice as large as for the robust group than the exposed group, it is necessary to control for (Table 2). The control for the unemployment level is introduced only in the interest rate cut period because unemployment varied severely during the cut period due to the first lockdown, when many people lost their jobs. During the interest rate hike period, unemployment did not have much variation. Hence, we do not consider the unemployment level in this period.

In model three, we add 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 on the high and low end of the liquid wealth distribution. We hypothesize that those holding large buffers are more robust to interest changes and have more ability to smooth consumption during the interest rate shocks. This is in line with the buffer-stock theory (Carroll, 1997), and implies that those who hold large buffers keep a more constant level of consumption.

Further, we include the control variable, *Debt Expander,* which identifies those who take up new debt in the period. As a result of interest rate cuts, credit becomes more accessible. Customers can increase their loans further when the interest rate is reduced. Our dataset shows that during the interest rate hike, the share who increase their debt is approximately equal between the robust and exposed groups. Oppositely, during the interest rate cut period, we observe that there is a higher share expanding their debt in the exposed group than in the robust group. Due to the nature of the financially robust group, there is a meager share who are credit constrained. Hence, they may borrow whenever they want to. In the financially exposed group, it is reasonable to assume that there is a significant share of credit-constrained individuals, due to the Norwegian lending regulations (Finansdepartementet, 2022). This pattern means that a larger share of the exposed group experiences going from being credit constrained to having access to increased credit. Some of them are likely to take advantage of this. Hence, they are likely to increase consumption in the subsequent months due to liquidity replenishment. The Debt Expander dummy captures this effect.

We also include a control variable to account for those residing in large urban areas. We do so due to the observed heterogeneity between the control and treatment groups in the proportion living in large urban areas. The consumption patterns of these individuals may also differ from those living outside of large urban areas. Any differences may be amplified since infection control measures were more restrictive in urban than rural areas during the COVID-19 pandemic. This is a factor relevant in both the interest rate cut and hike periods, since there was a lockdown, in at least some part of Norway, at some point during both periods, In model four, which for both the interest rate cut and hike period is our main model, we add several interaction terms between several of the covariates in previous models and the *post treatment* period. By doing this we mitigate the concern that those variables are subject to different trends during the analysis periods, due to other reasons 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 the interest rate changes. Furthermore, we introduce an interaction between *Debt Expander* and *Post* to control for trend differences between those who increase their debt during the period. We also introduce an interaction between *Large Urban Area* and *Post*, since 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 living in large urban areas, making this an important control variable.

6 Results

In Chapter 5.6, we provide the theoretical motivation for the model specifications. In this chapter, we present the results from those model specifications. The results will be presented separately for the interest rate cut and hike period. Since we log transform the dependent variable, we interpret the coefficients as percentage changes. As the independent variables are dummy variables, with the exception of the unemployment level, we do not log transform these.

6.1 The Interest Rate Cut Period

In Table 3, we report the estimations from our analysis of the interest rate cut period.

Our baseline model, model 1, suggests no initial difference in consumption between the groups in the pre-treatment period. We estimate an overall decrease in consumption in the post-treatment period, denoted by the *Post* coefficient. Such a decline is 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 to be 0.082. It is significant at the ten percent level. This indicates that the financially exposed group cut their consumption less than the robust group when faced with the interest rate cut at the beginning of the pandemic.

In Model 2, we add control variables for gender, co-dependency, unemployment level, and for being retired. The DiD coefficient, β_3, remains robust to these controls and is significant at the 10 percent level with a point estimate of 0.082.

In model 3, the DiD coefficient, β_3, is 0.081 and is significant at the ten percent level. The estimate is almost identical to the estimate in model 2. In model 3, we include three additional dummy variables to control for other characteristics, as mentioned in Chapter 5.6. We include a control for those holding a *Large Buffer*. This control variable is insignificant, meaning no significant difference exists between their consumption and those who do not hold a *Large Buffer*. We include a control for debt expanders, and we find that these individuals consume 24.2 percent more than the rest of the sample. The difference is significant at the one percent level. We also add a control variable for those living in large urban areas. We find that these consume 4.6 percent less than those who do not live in large urban areas. This difference is significant at the five percent level.

In model 4, our main model, we introduce several interaction terms that control for expected differences in the adaptation to the COVID-19 pandemic. The result of the DiD coefficient, β_3, is robust to including these control interactions and is significant at the ten percent level with a point estimate of 0.076. The point estimate of the *Debt Expander* control included in model four is reduced in magnitude compared to model 3, when the interaction term is included, and is no longer significant. The reduction is likely due to the fact that part of the effect occurred in the treatment period, reducing the pre-period estimate. Regarding the *Large Urban Area* variable, we observe a magnified negative effect, likely due to different trends between central areas and other areas during the pandemic. However, this period-specific trend is insignificant, as seen 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

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

Model 1 shows a baseline difference between consumption between the exposed and robust group of 5.1 percent, significant at the 10 percent 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-period, as indicated by the non-significant $Post$ variable, β_2. The DiD coefficient, β_3, *Exposed*Post*, is not significant, indicating no significant effect of the increased interest rate on 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 remain the same. There is still no significant effect of the DiD variable, β_3, *Exposed*post*.

In model 3, we add the same control variables as for the interest rate cut period. We show that those holding *Large Buffers* consume 5.9 percent more than those without. The difference is significant at the one percent level. *Debt Expanders* consume 16.2 percent more than those who did not expand their debt. This variable is significant at the one percent level.

In model 4, which is our main model also for the interest rate hike period, we include several interactions to account for differences in consumption development during the treatment period. Still, the DiD coefficient, β_3*, Post * Exposed* is not significantly different from zero. We add an interaction term between *Debt Expanders* and the post-treatment period. It shows no significant difference in consumption level between debt expanders and non-debt expanders during the pre-treatment period. However, this effect is very 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. Is is rather a more general pattern since the interaction term *Post*Large Buffer* is insignificant, while *Large Buffer* remains significant at the one percent 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 findings are that the interaction term between the exposed group and the post-treatment period is significant at a 10 percent significance level during the interest rate cut period, while it is not significant 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 compared to the robust ones. We find no significant effects from the interaction between exposed and post-treatment for the interest rate hike regressions, which indicates that the difference in the 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 include several interaction terms to add controls for unparallel trends between different sub-groups. It is important to add controls for interactions during both the interest rate hike and the interest rate cut period, as there may exist period-specific trends that correlate with the control variables, which may bias the estimates.

The determination coefficient for the models, R^2, remains very low throughout the analysis. The low exlanatory power does not need to be an issue and may only reflect that the confidence intervals of our models are very large, as 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 variable considerable variation. Personal preferences amplify this variation.

7 Robustness checks

In Chapter 4 and Chapter 5, we present several significant weaknesses with our dataset and what limitations and challenges these weaknesses impose to our analysis. To limit these concerns and increase our results' trustworthiness, we perform several robustness exercises that will take the main issues into account.

7.1 Parallel Trends

The parallel trends assumption is essential to DiD analyses. Given that the treatment- and control groups would have experienced parallel consumption trends in the absence of the interest rate shock, we can attribute any difference in consumption development to heterogeneity in the interest rate shock. Had the groups not had parallel trends, the analysis would contain bias. Hence, it is crucial to check the validity of this assumption. When analyzing consumption patterns and responses, it is even more critical since seasonal effects play such an important role. The seasonal effects on consumption between months may outweigh possible effects we may find from interest rate changes. It is also important to consider that seasonality may differ between the two groups based on heterogeneity in characteristics. If seasonality differs, the results may be biased. However, given parallel seasonal trends, the seasonality of consumption will not bias the analysis. We investigate the parallel trends assumption by plotting the pre-trends of the consumption twelve months prior to the interest rate changes for both the treatment and the control group. By plotting a full year of observations prior to the treatment, we capture any differences in the seasonal patterns efficiently.

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

Having parallel trends prior to treatment does not necessarily mean they would have continued in the absence of treatment, but it does provide a good indicator. We can also see that the original consumption levels were relatively similar, albeit slightly higher, for the exposed group during the pre-treatment period of the interest rate hike. For the interest rate cut, there was no significant difference between the consumption levels between the two groups. This strengthens the assumption that the two groups are similar enough to be comparable. However, as mentioned earlier, the financially exposed and robust groups differ on other observable covariates, which may bias the comparison since these differences may be correlated with consumption decisions but not with financial robustness.

7.2 Propensity Score Matching

In Chapter 5.4, we discuss heterogeneity between the financially robust and exposed groups. The differences in observed characteristics may be correlated with consumption decisions but not with financial robustness, which may bias our analysis estimates. We employ propensity score matching to add control for the heterogeneity on observed characteristics. Matching techniques allow us to alter datasets by choosing observations and weighing observations such that the groups become more balanced on given parameters. Choosing covariates to base the matching upon and selecting the matching method is critical to this data-generating process. First, we use optimal pair matching, a matching technique implemented by 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. The method matches at the observation level and, using logistic regression, it optimizes a distance criterion. The distance is optimized by choosing observations that share characteristics, which makes 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 is an imbalance between the two groups on these variables. Hence, they have the potential to bias our estimates. We use the variables *Gender*, *Private sector, Retired, Large Urban Area,* and *Co-dependent*. The imbalance can be seen from descriptive statistics in Table 2 and appendix 1, Table 6. When the datasets have been matched, we see an improvement in the balance of the summary statistics of these variables. We see this by comparing the balance for the full dataset in Table 17 to the matching output in Table 18[15]. The regression results for both the interest rate cut and hike period are robust to using datasets matched using optimal pair matching, as can be seen from Table 7 and Table 8.

We also test generalized full matching to see if the results are robust to an alternative matching algorithm (Ho et al., 2011). The generalized full matching technique is different from the optimal pair matching. It is a more powerful algorithm and matches the sample by splitting the observations into subclasses based on the likelihood of receiving treatment. It then weighs these subclasses differently in order to end up with control and treatment groups that are perfectly balanced on the covariates it matches on. The matching summary can be seen from the matching output in appendix 4, 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 a 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 since 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 using generalized full matching. However, the most extensive model is just shy of being significant for the interest rate cut period with a P-value of approximately 0.105 compared to approximately 0.085, which is the result in the main specification without matching. The 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 the results on the unmatched dataset. We

[15] 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 thesis.

report regression results based on matched data using generalized full matching in appendix 2, Table 9 and Table 10.

7.3 Two-way Fixed Effects

One concern with the simple two-groups, two-periods DiD estimation is that unobserved time and group invariant variables affect heterogeneity in 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 fixed effects and group level fixed effects. This prevents us from including controls for observable characteristics that are time-invariant within the exposed and robust group, as we do in the main model. However, this estimation technique enables us to control for the time and group invariant variables by adding group and month-fixed effects to the model. We estimate this model as Equation 6.

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

In equation 6, subscript i is a group indicator, and subscript t is a time indicator. α 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 the idiosyncratic error term.

The results of this specification for both the interest rate cut and hike can be seen in Table 11 in the appendix. They 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 period.

7.4 Interaction Tests & Placebo Regressions

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

When running the regression on other periods with no interest rate changes, we find no significant heterogeneity in consumption development between the exposed and robust groups. We examine two periods in which no interest rate changes occur to avoid capturing any interest rate effects. We set the first period to 2017 to compare our results to a placebo period in which there were no interest rate changes for an extended period of time. Additionally, it is during a different period, which tests the parallel trends assumption during a period with a different macroeconomic environment. The second period is from mid-2020 through mid-2021. We choose this period since it is close in time to our analysis periods. Thus, this regression can provide further insight into whether the parallel trends assumption is plausible (Figure 4). The results of these two sets of regressions show that when no treatment occurs, no significant differences in the heterogeneity of consumption development between the robust- and exposed groups are estimated. The results of these placebo regressions can be seen in Table 12.

We also perform a second set of placebo regressions in which we use different groups to assign treatment status. We perform a robustness check in selecting treatment groups based on different relative LTV levels. When choosing relative LTV levels close to the median rather than at the far ends of the distribution, there should be no significant effect from the regression. We choose the age-adjusted relative LTV quantiles between the 40^{th} and 50^{th} percentile as the control group and the 50^{th} to 60^{th} percentile as the treatment group. As expected, the results show no significant treatment effect of being treated, neither during the interest rate cut nor the interest rate hike period. The results of this set of regressions can be seen in Table 15 and Table 16.

7.5 Tests

We test for heteroscedasticity in all models by performing the Breusch-Pagan test. We find that the P-value for the test is below the five percent significance level, suggesting we should add control for heteroscedasticity. Hence, we use heteroscedasticity robust standard errors. Since we only consider two groups and they are not sampled in other clusters, we do not cluster the standard errors.

Multicollinearity is a potential concern for the analysis. We examine this in the correlation coefficient matrix (Figure 11 and Figure 12) and using variance inflation factor (VIF) scores. We observe non-worrying levels of correlation coefficients and multicollinearity. However, when we add multiple parameters, all interacting with the *post* variable, we get high VIF scores. This is expected, as interaction terms in which one variable is the same produce high VIF scores. However, this is not a concern since these interactions are merely controls and we do not have VIF issues in the level variables.

8 Discussion

In Chapter 6 (Table 3 and Table 4), we present our results which indicate a heterogeneous short-term consumption response between the robust and exposed groups following the interest rate cut in March 2020. We find that the financially exposed households with high LTV ratios increase their consumption more than the financially robust who have low LTV ratios. This is apparent since *Post*Exposed* in model 4 in Table 3 is positive and significant. Conversely, we do not find any heterogeneity in consumption development between the groups after the loan interest rate hike in December 2021 and January 2022. This can be seen from the insignificant *Post*Exposed* coefficient in model 4 in Table 4.

The positive result from the interest rate cut period is in line with the theoretical cash flow channel of interest rate changes. In line with this result, previous literature also estimates a significant cash flow channel. Conversely, the results contradict the cash flow channel during the interest rate hike period. This is because the financially exposed get a greater decrease in disposable income when the interest rate increases compared to the financially robust. However, we find no evidence that they reduce their consumption accordingly.

We must underline that these results are highly uncertain due to inaccurate data, a small sample size, and considerable heterogeneity between the groups as the primary causes.

Next, we will highlight some key mechanisms to 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 influence of forward guidance. These elements require further investigation to understand their implications fully.

8.1 The Cash Flow Channel: Overestimation

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

Given summary statistics on customers' loan size, average interest rate, and remaining installments, we calculate the average difference-in-differences 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, a strong assumption, the difference corresponds mathematically to a computed DiD coefficient of equation 1 of 2.2 percent (Table 22). Our model produces results around three to four times the size of the computed effect. However, we can only document significance at the ten percent level. This indicates that the effect we estimate is 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 in consumption between the two groups of about -1.5 percent (Table 22). Our model estimates that the DiD coefficient is not significantly different from zero. It follows from the results that in both the hike and cut period, the exposed group, relative to the robust group, spends a larger proportion of their disposable income on consumption after the interest rate change than they did before.

Our findings for the cash flow channel during the interest rate cut are sign-consistent (share the 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 these studies. During the interest rate hike period, we estimate no significant cash flow effect. Di Maggio et al. (2017) do not consider interest rate hikes, while Flodén et al. (2021) estimate interest rate shocks via a different method, in which the sign of the interest rate change is not important. Hence, our results contradict the results of Flodén et al. (2021) for the interest rate hike period. Both studies primarily study long-run effects, while we study short-run effects, which means they should not be compared. Overall, our results are much stronger than the average finding in the literature during the interest rate cut, while they are weaker during the interest rate hike.

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

One attenuating effect on 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 shows that some individuals choose to reduce their debt burden by voluntarily deleveraging their mortgage (Di Maggio et al., 2017). By taking advantage of the increased disposable income to make an unscheduled repayment, individuals can improve their financial situation by reducing their monthly expenses. Di Maggio et al. (2017) found that those with high levels of liquid assets were more likely to deleverage. They only had access to data for an interest rate cut and, as such, have not shown if this effect is symmetric for interest rate hikes and cuts. This reasoning suggests that the heterogeneous consumption response during the interest rate cut may be stronger if there is an overweight of robust individuals doing this. However, very few individuals we observe deviate from their repayment schedule, suggesting that this effect is negligible.

8.2 Heterogeneity in Risk Perception

One may ask if risk aversion influences how the two groups perceive their surroundings and make consumption decisions based on them. Given that risk tolerance and financial exposure are underlyingly correlated, the effect will either strengthen or attenuate the effects of monetary policy on private consumption. This topic is not well-researched in macroeconomics.

The robust and exposed groups differ in observable characteristics that are shown to be key in determining risk tolerance. Factors such as gender, income, and occupation are important to understand risk perception (Sahm, 2012). Since the exposed group has a larger share of men and a higher proportion occupied in the private sector, these are signs that the exposed group has a higher level of risk tolerance.

Furthermore, exposed individuals are higher leveraged (Table 2), which may partly be explained by their higher risk tolerance. This is in line with the findings of Sahm (2012), who finds a positive relationship between indebtedness and risk tolerance. From our data, we know that indebtedness is highly correlated with age. By using the relative LTV quantiles by age categories as our treatment group, we ensure that the difference in risk tolerance between the exposed and robust groups is not biased by 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 that is likely to contribute to the upward bias of the cash flow channel we observe in the results in Chapter 6. Next, we will discuss the channels that risk perception heterogeneity works through.

8.2.1 Substitution Effect

Heterogeneity in the groups' risk perception may affect 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 Chapter 5.5, highlights that an interest rate cut makes saving less attractive and encourages current spending. The opposite is true if the interest rate increases. Individuals' risk perception may affect how they rush or defer their consumption in line 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 explain part of the large point estimates during the interest rate cut period. Given homogeneous inflation expectations, the exposed, more risk-tolerant group chooses to substitute more of their consumption from the future to today relative to the robust group. On the other hand, when faced with an interest rate increase, the substitution effect should, in isolation, lower consumption and increase savings among the financially exposed. This is because this group has a higher level of intertemporal substitution, following Yagihashi and Du (2015).

Notably, the interest rate hike came simultaneously with fear of higher inflation expectations. As Duca et al. (2019) state, higher inflation expectations lead to an expected lower real rate of interest. Following this, according to the substitution channel, higher inflation expectations will make consumers spend more today and less in the future (Duca et al., 2019). However, Reiche and Meyler (2022) show that the 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 the robust group's, attenuating differences in their consumption response from intertemporal substitution following interest rate changes. Thus, it is unclear which sign the inflation effect has on intertemporal substitution during the interest rate hike.

8.2.2 Precautionary Savings Effect

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

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

Differences in precautionary savings may also affect differences in consumption responses during the interest rate hike period. There was a large degree of uncertainty during the interest rate hike period. During this period, the concerns of 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 shows 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 will be more likely to increase their precautionary savings and reduce consumption relative to the exposed group. This may partially explain why we do not observe any differences in consumption response during the interest rate hike period.

In isolation, precautionary savings dampen the overall interest rate effect on consumption, but due to heterogeneity in risk perception, the two groups save to different extents. This may contribute to explaining the results.

8.3 The Expectation Channel: Forward Guidance

Forward guidance of the policy rate, which works through the expectation channel, can partly explain why we only find a heterogeneous consumption response during the interest rate cut. By comparing the two periods of interest rate changes, the hike was anticipated, while the cut was unexpected. The different nature of these two interest rate changes suggests that only the interest rate cut can be considered an unexpected shock. Already from early 2021, Norges Bank prognosticated the policy rate hike through their forward guidance (Norges Bank, 2021a). Forward guidance is a tool adopted by central banks over the past decade in which they publish forecasts of future policy rates. Forward guidance gives transparency and predictability to economic agents, allowing them to adjust to future interest rate levels. The interest rate cut, on the other hand, came unexpectedly, preventing people from having the chance to adjust their consumption in advance.

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

Translated into our setting, this means that the robust group is more likely to have taken forward guidance into account compared to the exposed group. Therefore, the robust group is more likely to have adjusted their consumption before the interest rate hike, which may contribute to the insignificant differences in consumption responses in this period. (Druedahl et al., 2022) primarily looks at interest rate cuts, meaning that it is not obvious whether the pattern will be true for interest rate hikes as well.

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

8.4 Strengths and Weaknesses

8.4.1 Strengths of This Study

Our research design has several desirable features, which makes it an exciting contribution to the existing branch of literature. Microdata from a bank is not widely examined in this research field. Bank data has the primary advantage of granting us greater temporal resolution than what is typical in previous research. Access to monthly bank data allows us to examine the short-term effects in contrast to longer-term ones typically captured by yearly register data. Few studies have been done on the very short-term effects of monetary policy, which is a critical topic to understanding the effects of monetary policy fully. Our paper ventures into relatively unexplored grounds and is a new contribution regarding both method and dataset.

Collaborating with BN Bank has allowed us insight into a unique bank dataset. The bank has gathered data for purposes other than research for more than two decades. We have received precise information on the variables, in which some are imputed, and some are observed. Since we have had first-hand access to this data and to the employees in the bank that work with this daily, we have had a unique opportunity to comprehend the data fully. We know the strengths and limitations of the data, which in particular, is a great advantage of our thesis' methodological choices and possible issues that may arise from specific econometric estimation techniques.

The empirical DiD approach, in which we assign treatment to those who are relatively financially exposed compared to their age group, is a way to mitigate the concerns of a strong correlation with the life cycle of individuals. The treatment assignment is a strength of our research design, as it allows us to circumvent the problems that age and financial exposure in terms of LTV and DTI are inevitably correlated. Another strength is the choice of analysis periods and the short time span. By considering pre-treatment periods with no interest rate changes and post-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 the interest rate changes, any measured differences after the interest rate reset is due to heterogeneity in their adaptation to interest rate changes. This is a strength of our method.

The COVID-19 pandemic caused an abrupt shock to the economy, and Norges Bank lowered its interest rate with an unprecedented speed and magnitude. This shock is of great interest to analyze. The cut was sharp, sudden, and unexpected, meaning consumers could not adjust their consumption beforehand. Access to such an unexpected interest rate shock of such a magnitude is rare and valuable for research purposes.

8.4.2 Weaknesses and Limitations

Our study faces considerable weaknesses and limitations. In this section, we will go through these in further detail and comment on their implications.

Ironically, the strengths of this thesis are also some of its foremost weaknesses. The dataset we have employed limits our analysis because we do not have access to certain key variables that would have helped the analysis. We do not have a complete overview of individuals' balance sheets. As mentioned in several chapters, this disables us from observing deposits, spending, and stock or bond holdings in other banks. We partially overcome the issues by filtering out inactive customers from the panel. However, in line with a survey from Forbrukerrådet (2023), a significant portion of the individuals in the dataset likely have banking relationships outside of BN Bank, which limits our research in several ways. First, we cannot necessarily assume that the levels of deposits and spending we observe reflect a representative sample. Second, we do not have a reliable measurement of individuals' income, which has several implications. In combination with the fact that we do not have complete information on individuals' other banking relationships, we cannot compute a measure for savings, which would have been a valuable variable to analyze.

Due to the lack of data on income, we are forced to construct a measure of individuals' robustness without considering their income. Had we had access to income and savings data, we would be able to produce a much more detailed analysis with better measurements for financial robustness and a more reliable consumption measurement. In a 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 the coarse temporal resolution. This type of data lends itself more towards the use of a methodology like in Flodén et al. (2021) and Gerdrup and Torstensen (2018) that have a stronger focus on the full cash flow effect of interest rate shocks rather than a focus on short-term heterogeneous effects.

In terms of measurement precision, our data has several flaws, as several measurements are very coarse. Specifically, we cannot distinguish between the consumption of durable and nondurable goods since our data on durable consumption is imprecise to the degree that it is not meaningful to include. We cannot distinguish between goods and services or necessity and luxury goods either. Distinguishing between these goods would be very interesting since it would allow us to consider how different sectors may get hit heterogeneously by interest rate cuts. Additionally, it would enable us to consider the COVID-19 effect to a greater extent since the pandemic hit some sectors very hard while others grew (Figure 3). Also, several control variables, such as income and family structure, are only observed when individuals apply for loans. As these variables are updated infrequently, they are not sufficiently reliable, so we avoid using them. Further, we do not have data on the second income earner in households containing two adults. This impairs the analysis, as shared accounts and spending will not be accounted for. Also, household members may split consumption between them, which we cannot control for.

Since it typically is the man who is the main borrower, only observing the prime borrower also means that there is a gender imbalance in our panel, which hurts external validity.

Another concern is the sample's representativeness of the population. For instance, we know from the population pyramid that our sample is overrepresented in South-Eastern Norway (Figure 7) and amongst men, especially in the age span 40 to 60 (Figure 6). This skewness can potentially bias our results and imply challenges in providing external validity. This issue could be resolved by creating a sample that matches the population on certain key parameters. However, for the short time span we are analyzing, doing this from our sample would severely restrict our degrees of freedom.

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

The size of the dataset is another weakness of ours. Given that a change in interest expenses can change consumption only slightly, we depend on a large sample to achieve precise estimates. Factors such as income, wealth and seasonality affect consumption far more than the interest rate, which explains our models' low explanatory power, R^2. Our study comprises only around 2,000 individuals. Other studies that look into cash flow effects from interest rate shocks such as Druedahl et al. (2022), Flodén et al. (2021) & Gerdrup and Torstensen (2018) have datasets with hundreds of thousands of observations. Another challenge with the limited data size is that it limits our ability to analyze various sub-samples in the dataset due to loss of degrees of freedom.

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

The endogeneity of interest rates imposes some challenges for analyses. The policy rate is not solely determined by exogeneous factors, as central banks react to changes in economic conditions. Most notable are identification problems, in which we identify causal relationships. There is 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 unemployment level and inflation, makes it more challenging to establish clear causal relationships.

The context of our study, conducted during the COVID-19 pandemic, further complicates the analysis. Preventive measures restricted individuals' ability to maintain spending on certain types of goods, disproportionately affecting the consumption of services over goods (Figure 3). If the two groups initially have a different consumption composition of goods and services, it may cause bias to our estimates. Using generalized full matching partially allows us to mitigate 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 have chosen to take out a loan. It is unlikely that this choice is random and not correlated with underlying differences between the two groups. The willingness of individuals to take on larger loans and their associated exposure are likely to be correlated with their risk tolerance.

Given our dataset, which consists only of mortgagors, and using the interest rate resets as treatment timing, we partly violate the assumption that the control group remains untreated throughout the period since this group also will face an interest rate change. The control group will receive treatment to a smaller extent than the treatment group, meaning there is still a sizeable treatment effect. However, due to using the age-adjusted relative LTV as an indicator of receiving treatment or not, 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) compare indebted households with debt-free households, effectively having one group that is only affected by interest revenue and not by interest expenses. We use a control group that is also treated to some extent. This can be justified by the fact that the alternative group, the ones without mortgages, is likely, not comparable. In Norway, such households stand out as being a homeowner is so predominant, as seen in Figure 2. Thus, those who do not own homes are unlikely to be comparable to those who do. Another alternative comparison group is those with FRMs, who will be unaffected by an interest rate change in the short-term but are still homeowners. However, this is not a viable approach since the share of FRM holders is extremely low in Norway (Statistics Norway, 2023e).

8.5 Implications and Further Research

The fact that the very short-term effects of monetary policy are studied to a limited extent is one of the main reasons why this thesis is of interest. We point out a possible option for how to conduct research in this interesting and relatively unexplored part of the literature, by using administrative bank data.

In accordance with Norges Bank's targets, as described in Chapter 3.1, it is of interest to understand the consequences of monetary policy completely. This also includes solid understanding of the very short-term, one to three months, effects. Insight into the sluggishness of the short-term adaptation to interest rate changes is valuable. Monetary policy overreacting is a notion referring to the concept when central banks make one interest adjustment too many. Such overreacting may occur if the central bank does not fully understand the consequences of the previous interest change before conducting the next one. Further research on how the economy responds in the first 1-3 months following interest rate changes may impact monetary policy. Our study does a limited job of answering these questions, but we provide some indications that the effects are not symmetrical for individuals with different financial vulnerabilities. We shed some light on this field and point out the need for further research on this subject.

As the financially exposed group in our sample is higher leveraged, they pose a greater risk to financial stability. Regarding Norges Bank's target of mitigating 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 the consumption of exposed individuals. Since we do not find significant results during the interest rate hike period, we do not find evidence that such a pattern exists in the short run. Furthermore, the results of the analysis may improve the commercial banks' risk models. The banks' exposure is directed toward mortgages secured by residential real estate. To withstand economic downturns, it is valuable for the banks to gain insight into mortgagors' consumption patterns and how their ability to service their loans is affected by changes in interest rates.

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 when faced with interest rate cuts relative to the robust group, as is suggested by the cash flow effect. The results also show that the exposed group contrastingly does not tighten their private consumption symmetrically when faced with an interest rate hike. Given that these effects remain in the long run, they imply that for each interest cycle, the discrepancy in financial robustness between exposed and robust groups will only accelerate. This feature is not desirable because central banks focus on promoting financial stability. This may have implications for how central banks consider heterogeneous risk aversion when adjusting monetary policy.

As mentioned in the previous chapter, our main concerns are related to data. One may resolve some of this study's shortcomings by getting access to data from a larger bank. A larger dataset will allow one to select more comparable treatment groups and achieve more precise estimates. An approach could be to send out surveys to a representative sample of banking customers to get data on other important characteristics that are, by default, unobserved to the bank. The survey data could be paired on an individual level with the administrative bank data. One could also ask if they have other banking relationships, and in case they are co-dependent, one could cluster households together. Alternatively, pairing administrative register data with bank data, as in Druedahl et al. (2022), is a step that would solve many of the issues we have dealt with. Such a data foundation would enable us to estimate short-term effects more precisely and confidently. Several other minor steps would improve the study, such as clustering on the household level and getting a better granularity of the consumption measure.

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

9 Conclusion

The purpose of this master's thesis is to analyze the short-term heterogeneity between how financially robust and financially exposed groups change their consumption when faced with interest rate changes. The topic has received relatively little attention in existing literature. We hypothesize that the exposed group has a stronger consumption response to interest changes than the robust group, in line with the cash flow effect. The cash flow effect theorizes that there will be a consumption response from interest rate changes through changes in disposable income, in addition to other interest effects, such as intertemporal substitution.

To undertake the analysis, we have employed a dataset from BN Bank with monthly observations on mortgagors. To separate interest rate effects from other macroeconomic trends, we use a DiD research design in which the treatment group is financially exposed, and the control group is financially robust. We measure financial exposure as LTV relative to age group. Assigning treatment groups based on this measure is a new approach and mitigates the problem of the correlation between the life-cycle of individuals and financial robustness, which is an inevitable link. Our dataset has a high temporal resolution, which is advantageous when estimating short-term effects. However, it lacks the overview and completeness of administrative register data, as we do not observe the full balance sheets of the individuals in the sample.

We analyze both an interest rate cut and a hike to study if any differences in consumption responses between the two groups are symmetrical when disposable income is increased and reduced. We find that financially exposed consumers increase their short-term consumption relative to the financially robust group when faced with the interest rate cut in March 2020, albeit the significance is very weak. This is in line with the cash flow channel and what previous literature has found. Interestingly, we find that during the subsequent interest rate hike in the fall and winter of 2021-22 the financially exposed group did not differ in their short-term consumption trend compared to the financially robust group. This result contradicts the existing literature on the long-term cash flow channel.

Due to the inaccuracy of our results and the challenges concerning our dataset, there is not sufficient empirical evidence to attribute the results solely to the cash flow channel. Instead, we point to several channels that plausibly affect consumption heterogeneity. We highlight risk aversion heterogeneity, which particularly affects expectations through forward guidance and the substitution channel. These channels are plausible contributors to the overestimation of the short-term cash flow channel. It is likely that the limitations of our data contribute to the overestimation of the results. Specifically, issues arise primarily due to the coarseness, representativeness, sample size, and lacking variables.

Our results remain significant or almost so, depending on the specification, even after employing severe matching techniques and TWFE DiD to add control for said heterogeneity. This indicates that other unobserved, time variant effects affect how the two groups perceive interest rate changes heterogeneously. Delving into these effects is a topic left for future research.

The most important implication of this study is that it points out the need for further research. The most important issue to resolve in our paper is to gather better data to allow more precise and elaborative analysis. Conducting further research to gain an improved understanding of the immediate effects of monetary policy is valuable. It may help central banks not overreact in their monetary policy decisions and lead to a better understanding of how quickly monetary policy passes through to the economy. Our results also point to a need for research on how risk aversion affects monetary policy pass-through on the individual level. If the most financially exposed individuals are also the most risk-tolerant, it may have implications for financial stability.

Ultimately, this study provides some 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 adaptations. We hope other scholars will pick up where we leave and look into this topic with better data.

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Appendices

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*
	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:

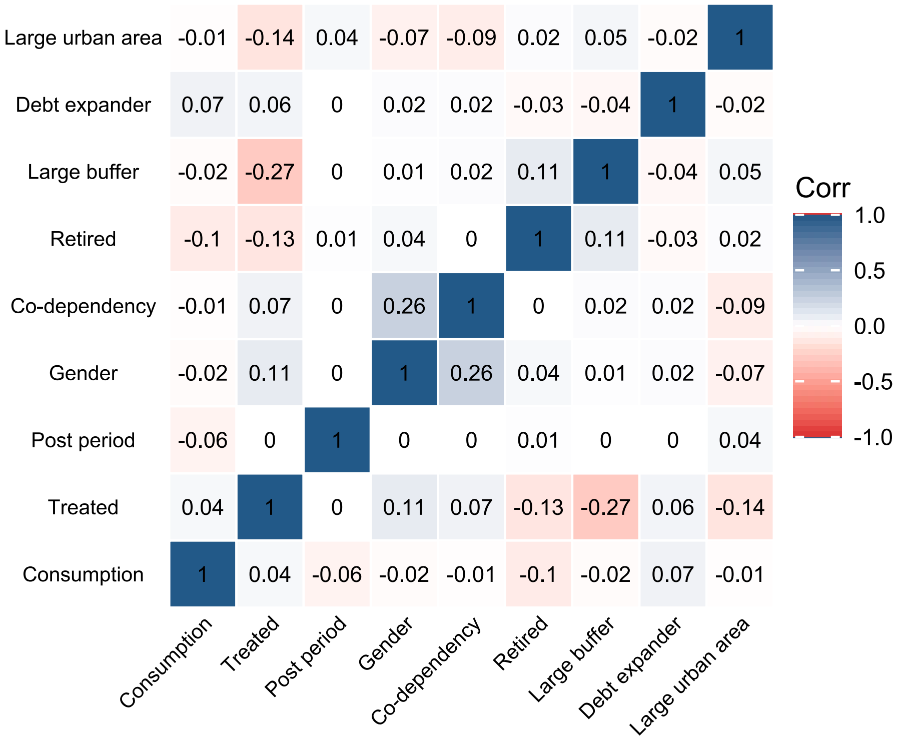
		Oslo, Bærum, Asker, Lillestrøm, Lørenskog, Nordre Follo, Rælingen, Nittedal, Lier, Bergen, Stavanger, Sandnes, Sola, Randaberg, Trondheim, Fredrikstad, Sarpsborg, Drammen, Øvre Eiker, and *Holmestrand*. Retrieved from Statistics Norway (2023a).
	Large Buffer	The customer holds deposits, including checking 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

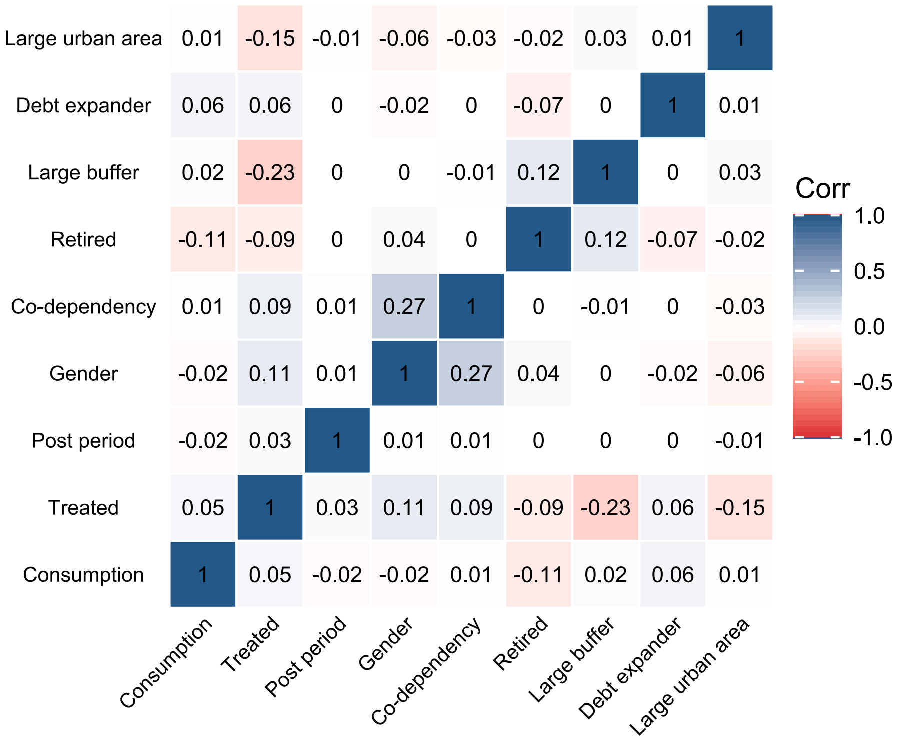
	Exposed individuals (N=962)	Robust individuals (N=1103)
Consumption (NOK)		
Mean (SD)	17,000 (± 8,000)	15,900 (± 7,800)
Median [Min / Max]	16,400 [0 / 41,000]	15,000 [0 / 42,300]
Deposits (NOK)		
Mean (SD)	143,700 (± 351,800)	295,800 (± 488,200)
Median [Min / Max]	44,800 [0 / 7,084,800]	127,000 [0 / 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.



Computed on entire sample in interest rate cut period.

Figure 11: Correlation Coefficient Matrix – Cut Period



Computed on entire sample in interest rate hike period.

Figure 12: 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.

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