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The Cash-Flow Channel of Monetary Policy - Evidence from Billions of Transactions*

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Abstract

We present novel findings on the impact of monetary policy on consumer spending behavior using a newly assembled high-frequency household expenditure panel. Leveraging comprehensive weekly electronic transaction-level data for all individuals in Norway over 13 years, our study sheds light on the high-frequency consumption response to monetary policy through changes in fast-moving net interest expenses. We employ several identification strategies, including household–specific interest rate shocks arising from a natural experiment and high-frequency monetary policy instruments. We find a substantial short-run consumption response to changes in interest payments. Relative to households with no interest exposure, households at the 90th percentile cut consumption by $1 - 1.5$ percent of income within a year of a 1 percentage point policy rate hike. Our results imply a substantial marginal propensity to consume out of net interest payments, and they indicate the presence of a strong cash-flow channel of monetary policy.

Keywords: Monetary policy transmission, Household Consumption, Debt, Interest rates, Marginal propensity to consume, High frequency

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1 Introduction

What is the role of household debt in the transmission of monetary policy? In recent decades, household debt has outpaced income growth in many developed economies, pushing debt-to-income ratios to historically high levels. While a growing literature (Mian et al., 2013; Jordà et al., 2016) has shown that household leverage can amplify macroeconomic fluctuations, it remains unclear how increased household indebtedness affects the speed and effectiveness of monetary policy transmission. Since monetary policy transmits rapidly to interest rates on adjustable-rate loans, an increase in debt-to-income ratios means that a greater portion of household cash-flows become directly exposed to policy changes, potentially magnifying the impact monetary policy has on aggregate demand. In this paper, we offer empirical evidence on how debt influences monetary policy transmission by examining how the responsiveness of household consumption to interest rate changes varies with interest exposure.

In standard macroeconomic models, cash-flow fluctuations have only a minimal impact on consumption. Rational agents with frictionless access to capital markets adjust consumption smoothly in response to monetary policy-induced income changes. In the workhorse New Keynesian model (e.g. Clarida et al. (1999) and Christiano et al. (2005)), monetary policy mainly transmits to consumption through the intertemporal substitution channel, while income effects are small.[1] In contrast, recent theoretical (Kaplan et al., 2018) and empirical (Di Maggio et al., 2017; Flodén et al., 2020; Cloyne et al., 2020; Holm et al., 2021) advances suggest that households' balance sheet positions are pivotal in transmitting monetary policy shocks to household consumption. Nevertheless, the empirical understanding of the role of debt in transmitting monetary policy remains limited, primarily due to demanding data requirements. The ideal setting, which rarely exists, requires high-frequency household-level spending linked to detailed balance sheet positions over time.

The Norwegian economy, with its extensive administrative records, offers an unique opportunity to tackle this data challenge. In this paper we combine household balance sheet and income information from high quality tax records with a newly assembled high-frequency electronic expenditure database. Our dataset contains detailed information on wealth, debt, income, and demographics, merged with weekly debit card purchases and online bank wire transactions for nearly every individual in Norway between 2006 and 2018. As Norway is virtually a cashless economy, the transactions data, covering nearly 80 percent of electronic expenditures, provide a

[1] This is demonstrated by Kaplan et al. (2018), among others.

comprehensive measure of household-level consumption. Its high-frequency nature also enables measurement of the short-term responses to monetary policy and makes it possible to overcome a potential temporal aggregation bias by aligning the timing of the shock with the outcome variable, as discussed in Buda et al. (2023) and Jacobson et al. (2022).

With the rich micro level data at hand, the paper proceeds with investigating the role of debt for the transmission of monetary policy to household consumption. We do so by estimating how household level variation in interest payments, induced by interest rate changes, transmit to consumption. Higher interest rates increase the interest payments of borrowing households with adjustable-rate debt, resulting in reduced cash-flows and potentially lower spending. At the same time, higher interest rates increase the interest earnings on deposits, increasing the cash-flow of depositor households.[2] The credit and housing markets in Norway provide an ideal setting to study this cash-flow channel of monetary policy. Compared to most other developed countries, Norway has a high rate of homeownership and a high debt-to-income ratio among households. Around 90% of household loans and bank deposits have floating interest rates that are adjusted quickly in response to movements in the policy rate. Hence, our measure of interest exposure – the difference between gross debt and deposits – is closely related to the measure of unhedged interest exposure that Auclert (2019) shows is the correct measure of a household's balance sheet exposure to real interest rate movements.[3]

In order to address the inherent endogeneity associated with interest rate changes, we approach the research question using several identification strategies. Following a large empirical macro literature studying the impact of monetary policy (see e.g. Ramey (2016)), the first two approaches employ local projection methods à la Jordà (2005) to estimate the dynamic impact of a change in the policy rate on household-level consumption at a monthly frequency. We interact movements in the policy rate with household interest exposure, creating a proxy for changes in interest payments. To address endogeneity issues arising from monetary policy reacting to changes in macroeconomic conditions, we use two separate local projection specifications. In the first specification, we include time fixed effects interacted with granular group level characteristics to account for the confounding macroeconomic environment. These fixed effects also control for other transmission channels of monetary policy that might covary systematically with interest exposure, allowing us to separately identify the cash-flow channel.[4] Furthermore, indirect effects

[2]This definition of the cash-flow channel of monetary policy follows La Cava et al. (2016), Flodén et al. (2020), Cloyne et al. (2020), Slacalek et al. (2020) and Tzamourani (2021).

[3]See also the simple exposition in Slacalek et al. (2020).

[4]For instance, highly indebted households might also be more likely to lose their job when aggregate demand drops. To the extent that the observable characteristics we include in the regression capture the likelihood of

of monetary policy on consumption operating through general equilibrium effects are likely not very strong at horizons shorter than one year, as shown empirically for Norway by Holm et al. (2021). In the second identification approach, we construct a new set of monetary policy instruments for the Norwegian economy and use them in an instrumental variable setup as in Stock and Watson (2018). We partition households into bins based on their position in the interest exposure distribution and estimate local projection instrumental variable (LP-IV) regressions for each group and time horizon separately. We instrument the interest rate movements with high-frequency monetary policy surprises in the spirit of e.g. Kuttner (2001) and Gürkaynak et al. (2004), and we follow Miranda-Agrippino and Ricco (2021) in removing a potential information component of monetary policy announcements.

In the third identification approach, we measure changes in interest payments resulting from household-specific shocks to mortgage rates arising from a natural experiment unrelated to macroeconomic conditions. The experimental setting offers two main benefits compared to the earlier methods, alleviating potential measurement and endogeneity concerns. First, rather than relying on proxies, we now observe both interest payments and borrowing rates directly in the data. Second, the identifying variation in interest expenses arises from changes in the cross-sectional dispersion of lending rates. The natural experiment involves a mortgage bank serving exclusively public sector workers, which prior to March 2014 offered highly subsidized mortgage rates relative to those offered in the private sector mortgage market. The government decided in the fall of 2013 and subsequently in 2014 to cut this subsidy considerably, inducing a sharp rise in mortgage rates in both March 2014 and subsequently in March 2015 for customers of the public sector bank only. Over this period, the subsidized rate was still lower than the rates offered in the conventional mortgage market, so customers of the public sector bank were not incentivized to switch to a private sector bank. Using detailed information on household bank connections, we then compare the evolution of consumption and interest payments for households with mortgages in the public sector bank with customers of other banks. This allows us the estimate the marginal propensity to consume (MPC) out of interest expenses.

From the local projections of consumption on interest rate changes, we observe that the impact of higher interest rates is more pronounced for households with higher interest exposure and more debt. The impact is both rapid and quantitatively important. From the fixed-effects specification, we find that 100 percentage points higher net debt relative to income is associated with a roughly 0.2 percentage points larger drop in consumption relative to income one year after

unemployment, we control for this confounding effect.

a 1 percentage point higher interest rate. These results imply that the median household will decrease its consumption by around 0.3 percentage points more than one with equal amounts of debt and deposits. Households with no debt and deposits display almost no change in consumption, while those at the 90th percentile of interest exposure reduce their consumption by $1 - 1.5$ percent of income after one year. The effect unfolds gradually throughout the year following a monetary policy change, with only small consumption responses within the first few months. When partitioning households based on net interest exposure and instrumenting for monetary policy, we find that cash-flow effects are present along most of the interest exposure distribution, suggesting that it is not primarily driven by households with exceptionally high levels of debt. However, when splitting net exposure into gross debt and bank deposits, our results indicate that debt is more important than deposits for the pass-through of interest rate changes to consumption. Moreover, while the average response in the first few months following an interest rate change is largely driven by households with low or medium levels of liquidity relative to income, by the end of the year, consumption responses appear similar across the entire liquid wealth distribution.[5]

The marginal propensity to consume is a central object of interest for macroeconomic policy. While there is a large literature on the MPC out of cash windfalls, wealth fluctuations and temporary labor market shocks, less is know about the MPC out of interest payments.[6] A back-of-the-envelope calculation based on the results from our first two identification methods and assumptions about the pass-through of policy rates to lending and deposit rates gives a yearly MPC in the range $0.185 - 0.38$.[7] Given that the typical interest rate change we consider subsides within one to two years, these responses are by all accounts considerably larger than those predicted by the permanent income hypothesis. However, the magnitude is in line with cash windfall MPC estimates based on nondurable consumption (e.g. Parker et al. (2013)), while at the low end of estimates based on total consumption (e.g. Fagereng et al. (2021)). Furthermore, we estimate MPCs of a similar size based on the natural experiment. Relative to households with comparable characteristics, customers of the public sector bank experienced a significant increase in interest payments, amounting to $912 in 2014. These changes were entirely driven by

[5]That the consumption response is not concentrated among the cash-poor households aligns with findings from other studies in which cash-rich households display excess sensitivity of consumption to income fluctuations. (Kueng, 2018; Olafsson and Pagel, 2018; Fagereng et al., 2021; Lewis et al., 2024; Andre et al., 2024).

[6]For estimates of the MPC out of cash windfalls, see e.g. Parker et al. (2013), Fagereng et al. (2021). For wealth fluctuations, see e.g. Chodorow-Reich et al. (2021). For labor market shocks, see e.g. Andersen et al. (2023).

[7]Since our consumption measure is derived from spending data on both durables and non-durables, this MPC is often referred to as the marginal propensity for expenditure (MPX), distinguishing it from the flow-based notional consumption measure typically considered in most models of consumption behavior (Laibson et al., 2022).

the relative changes in mortgage rates induced by the 2014 policy reform. In response to these movements in interest expenses, we find that customers of the public sector bank reduced their 2014 consumption by $278 more than comparable households in the control group, implying an average MPC of 30 percent.

Our findings carry significant policy implications. We demonstrate that changes in policy rates can have a substantial impact on household spending within a year of the policy change. This effect is likely more pronounced in countries like Norway, where adjustable-rate loans are common, than in countries like the United States, where long-term fixed-rate mortgages are prevalent, leading to more muted and delayed cash-flow effects in the latter. Furthermore, increasing debt-to-income ratios in many economies in the last few decades have likely amplified the sensitivity of household spending to shifts in monetary policy.

Our paper contributes to several strands of the literature. First, our results shed light on the role played by housing markets, mortgage markets and mortgage debt in shaping the transmission of monetary policy to the real economy. Using cross-country identification, the International Monetary Fund (2024) finds that transmission is stronger in countries where, like in Norway, fixed rate mortgages are not common, where home buyers are more leveraged and where household debt is high relative to disposable income. This aligns with other cross-country results reported by Calza et al. (2013), Alpanda et al. (2021), Corsetti et al. (2022), and Pica (2023). Alpanda et al. (2021) find that the effect of monetary policy on GDP is stronger in periods when the household debt-to-GDP ratio is above its long-run trend, but only in countries where adjustable rate mortgages are the norm. Compared to these cross-country studies, our micro data and identification methods allow us to isolate the cash-flow channel and control for other characteristics that might influence how households react to monetary policy.

Second, we contribute to the literature estimating the transmission of monetary policy to household consumption at the micro level. In particular, we provide estimates of the interest rate exposure channel described theoretically by Auclert (2019). Like Flodén et al. (2020), Cloyne et al. (2020), Holm et al. (2021), Di Maggio et al. (2017) and La Cava et al. (2016), we find an important role for mortgage debt in the transmission of monetary policy shocks to consumption. Unlike prior studies that utilize either survey data (Cloyne et al. (2020) and Wong et al. (2019)), impute consumption expenditures from annual tax returns data (Holm et al. (2021) and Flodén et al. (2020)), or use a subset of expenditures (Di Maggio et al. (2017)), we construct a consumption variable that is directly measured, captures most of a household's spending and is observed at a high frequency that aligns with the timing of monetary policy shocks. As such, we also contribute to the literature that estimates the high-frequency responses of aggregate variables to monetary policy shocks. Like Buda et al. (2023), we find that changes in monetary policy can transmit to household consumption more quickly than many previous studies utilizing quarterly or annual variables have found.

Third, we contribute to the literature estimating the marginal propensity to consume. Our estimated average MPC is sizable, echoing a large literature on MPCs out of other types of income shocks of varying persistence. For example, recent work on the consumption response to unemployment shocks report MPCs in the range $30-50$ percent (Andersen et al., 2023; Patterson, 2023; Fagereng et al., 2024). Using monthly wage fluctuations, Ganong et al. (2020) find average MPCs of around 23 percent for nondurable consumption. MPCs of similar magnitudes are often estimated based on windfall income gains (Parker et al., 2013; Jappelli and Pistaferri, 2014; Parker, 2017; Aguiar et al., 2020; Fagereng et al., 2021; Gelman, 2022; Boehm et al., 2023; Hamilton et al., 2023; Borusyak et al., 2024; Orchard et al., 2024). Several of these studies find some role for liquidity in explaining variation in MPCs between households, consistent with the mechanism present in HANK models. However, a growing body of empirical work finds high MPCs also for the cash rich (Kueng, 2018; Olafsson and Pagel, 2018; Andre et al., 2024; Lewis et al., 2024), while quasi-experimental evidence shows excess consumption sensitivity to predictable declines in cash-on-hand (Ganong and Noel, 2019; Gerard and Naritomi, 2021).[8] Our finding of sizable consumption responses to monetary policy also for liquid households is consistent with these studies.

The paper proceeds as follows. In Section 2 we present the our linked expenditure data and administrative records. In Section 3 we estimate how the response to common interest rate changes vary with household debt, controlling for endogeneity using fixed effects and high-frequency monetary policy instruments. In Section 4 we utilize the natural experiment giving cross-sectional variation in lending rates between treated and non-treated households. In 5 we conclude and discuss some policy implications of our results.

2 Data

We combine macroeconomic data with individual level register data from Statistics Norway and electronic expenditure data. This section provides an overview of each of the data sources and explain the criteria used to construct our analysis sample.

[8]The consumption response to predictable declines in income is particularly hard to reconcile with hand-to-mouth behavior among consumers, since even these types of agents should save in anticipation of such events.

2.1 Expenditure Data From Electronic Transactions

This section outlines in detail our electronic payments database, which includes most card and bank wire transactions for all Norwegian residents. We start by explaining how the database was collected and organized in 2.1.1. Then, in 2.1.2, we discuss the payment coverage and show that it contains about 80 percent of all electronic payments made by Norwegian households during the period 2006-2018. We finally show that our consumption measure derived from electronic transactions is highly correlated with household consumption in the National Accounts.

2.1.1 Data sources and Structure

The payments data are provided by the Norwegian retail clearing institution, Nets Branch Norway (henceforth abbreviated by Nets). Our data broadly covers two distinct types of payments, both aggregated by the data provider to the level of person, week, postal code (4-digit) and consumer category.[9] Appendix A contains further details on the structure and aggregation.

The first payment type consists of debit card payments made via the national payment processing system BankAxept. In the time period for which we have data, the near universe of debit card transactions at physical domestic stores were processed using this system.[10] We observe the purchase amount, number of transactions, and cashback (cash withdrawals at point-of-sales) for a combination of location and consumer category. The second payment type is individuals' bank wire transfers cleared via the Norwegian Interbank Clearing System (NICS) for the Norwegian krone (NOK).[11] Typically, most forms of invoice payments are processed by this system. We observe the total weekly transfer amount and number of transfers by a given person to a given combination of location and consumer category. Our dataset includes all Norwegian residents who made a debit card transaction processed by BankAxept or a bank wire transfer cleared by NICS in the period $2006 - 2018$.

2.1.2 Coverage and Cleaning

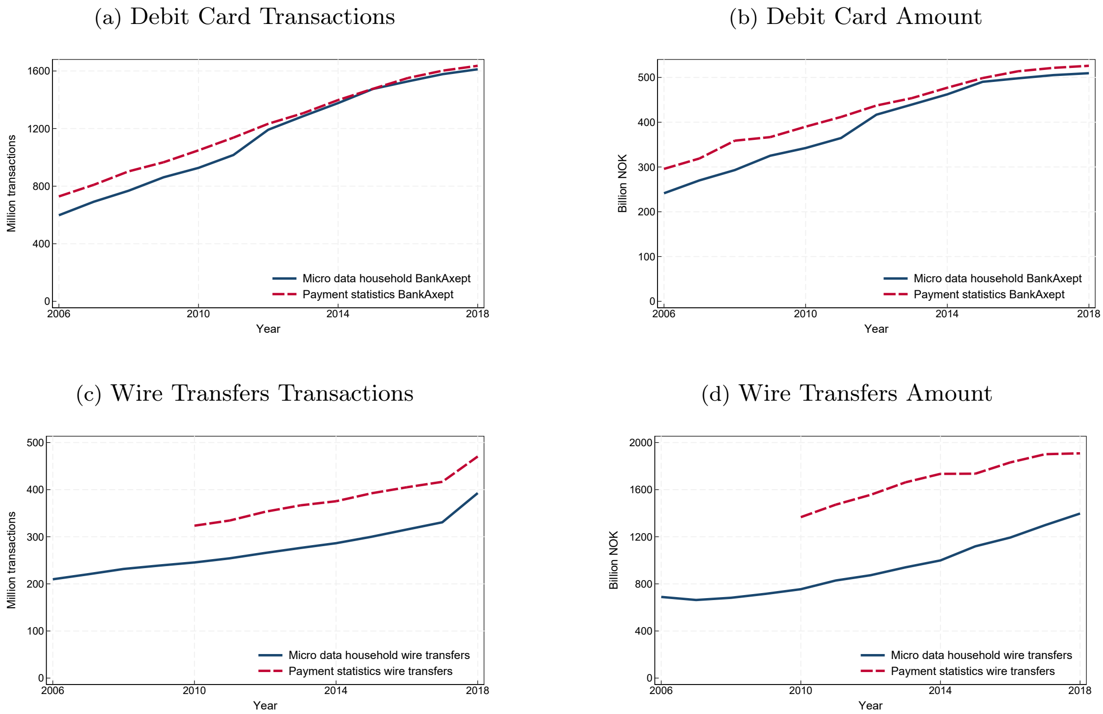
Debit Card Transactions (BankAxept) In Figure 1, panel (a) and (b), we plot the annual time series of the total number of transactions and their value, respectively, in the debit card database, along with official payment statistics (Norges Bank, 2023) on BankAxept debit card

[9] The consumer categories are based on 24 COICOP groups. In addition, wire transfers to the government and banks are placed in two separate categories

[10] In contrast, debit card payments made abroad, online, or via mobile platforms were processed mainly by VISA or Mastercard. These are not part of our dataset.

[11] NICS is used by all banks operating in Norway and that take part in the Norwegian banking community's infrastructure for payments.

Figure 1: Transactions and Amounts.



(a) Debit Card Transactions

(b) Debit Card Amount

(c) Wire Transfers Transactions

(d) Wire Transfers Amount

Notes. This figure shows aggregate number of transactions and the total transaction amount from two sources. The solid line represents the aggregated volumes over all households in our data base. The dashed line represents the official numbers reported in Norges Bank (2023). Panel (a) and (b) show debit card transactions processed using BankAxept. Panel (c) and (d) show bank wire transfers. The split between firm and household wire transfers is only available from 2010 in the official statistics.

payments and cashback. From 2012 and onward our dataset covers close to the universe of household debit card transactions. Prior to 2012 the coverage is somewhat lower. The reason is that Nets Branch Norway did not retain information on bank account owners for accounts that were closed prior to 2012. Transactions using debit cards linked to such accounts therefore do not show up in our database. However, as shown in Figure B1, the number of debit card transactions per user does not jump between 2011 and 2012.[12] Consequently, the unobserved transactions before 2012 primarily stem from individuals who are entirely absent from the dataset.This is reassuring for us, as it means that our household level dynamics is unlikely to be influence by this break in the data.

Bank Wire Transfers In Figure 1, panel (c) and (d), we plot annual time series for total number and value of bank wire transfers. From panel (c) we see that our data tracks the

[12]The most likely reasons for bank account closures during the 2006–2011 period are deaths or migration abroad.

official statistics closely, but with a gap. On average over time, our data covers 77 percent of all transfers. The reason we do not have full coverage is that not all bank wire transfers are processed by NICS. In particular, wire transfers between owners of accounts in the same bank are sometimes (depending on the bank) processed by the banks themselves.[13] The jump in the number of transfers occurring in 2018 is due to the introduction of peer-to-peer mobile transfers. To avoid double counting of spending we remove transfers between individuals from our data.[14]

In Panel (d) we see that the coverage is somewhat lower based on value than based on the number of transfers. On average our dataset covers around 60 percent of the value in the official statistics. It is important to emphasize that the total value based on the microdata is highly sensitive to the inclusion of very large single transactions.[15] As these are unlikely to reflect consumption expenditures, we clean our data by removing single transactions with a value above $100,000$ NOK (12,500 USD2015). In addition, we remove all transfers made by households to banks, observed in consumption category 13 (see Table A2). However, as explained below, we retain from category 13 an imputed measure of payments of credit card bills.

Credit Card Imputation While our card transaction data does not include credit card transactions directly, our wire transfer data encompasses payments made directly to banks. The main source of such payments are related to debt service, including mortgages and credit card bills. In Section C we explain the algorithm we use in order to separate between payments related to credit card bills and those related to regular debt service. The imputed credit card bill payments are retained in our expenditure measure, whereas regular debt service is removed. Figure C4 shows the imputed credit card payments and compare it to official statistics on credit card payments in Norway.

Total Card Payments Coverage Lastly, we evaluate the proportion of total payment card transactions covered by our debit card and imputed credit card payments. Debit card transactions processed through BankAxept covers the majority of card payments in Norway. Typically, all debit card payments in domestic physical stores are processed through BankAxept, whereas debit card payments abroad, online payments and mobile payments are processed through VISA or Mastercard. Figure 2 shows that BankAxept debit card payments account for more than 80

[13] These transfers are included in the official statistics, which are based on account-to-account transfers reported directly by banks.

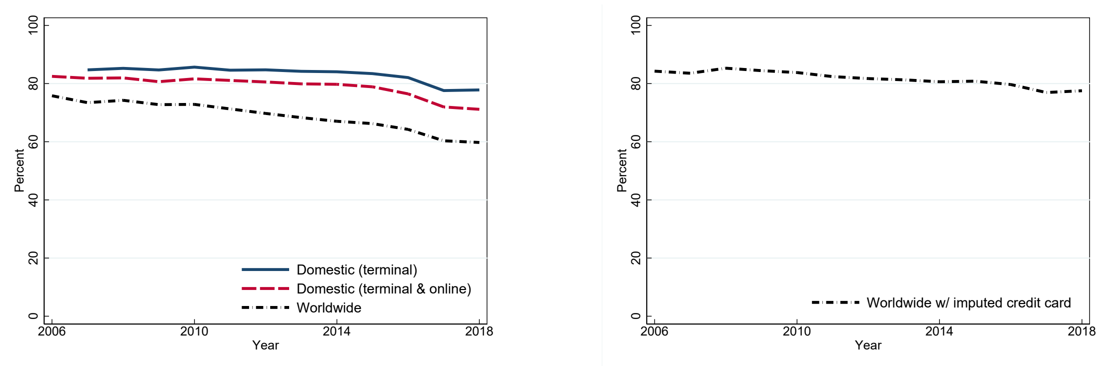
[14] This is done by removing all wire transfers that are missing both COICOP and location information.

[15] In fact, in both 2009 and 2011 there is a single transfer in our wire transfer database that accounts for more than 5 percent of the total value reported in the official statistics.

Figure 2: Total Card Coverage.

(a) Debit Card

(b) Debit Card and Imputed Credit Card



Notes. Panel (a) plots the share of total card payments (value of transactions) in (i) domestic card terminals, (ii) domestic card terminals and online payments and (iii) domestic and foreign terminals and online payments, that is covered by our debit card measure. Panel (b) plots the share of total card payments (value of transactions) worldwide covered by our debit card and imputed credit card measure. Aggregate statistics on Norwegian households' card usage are published annually by Norges Bank (Norges Bank, 2023).

percent of card payments in Norwegian in-store terminals. Adding online payments, which is not covered by BankAxept, the share drops by only a few percentage points, illustrating that online payments were not used extensively during our sample period. Finally, if we consider all card payments made by Norwegian households regardless of point of sale, the BankAxept share is on average around 70 percent, with a negative trend over the sample period. This negative trend reflects the increased usage of credit cards. However, when we add our imputed credit card measure, panel (b) shows a stable coverage rate of around 80 percent throughout the sample period.

Cash payments A potential concern with our spending measure is that (with the exception of in-store cashback) it excludes cash payments. To the extent that cash is an important unobserved payment method that systematically varies across people, such mismeasurement could contaminate the empirical analysis. However, this is less of a concern in our setting, since Norway is among the countries in the world with the lowest share of cash transactions in total payments. Survey data show that only 1 in 10 point-of-sale payments in Norway was made with cash in 2017 (Norges Bank, 2023). In contrast, the Euro area average was 4 out of 5 payments made with cash, with all countries (except the Netherlands) reporting cash as the most frequent in-person payment methods (Esselink and Hernández, 2017).[16] Statistics on cash-in-circulation indicate a similar pattern. Similarly, cash-in-circulation remained nearly constant in Norway between

[16]By value, the corresponding averages were 3 percent in Norway and 53 percent in the Euro area.

2001 and 2018, while most other OECD countries (with the exception of Sweden and Denmark) experienced a significant rise in the cash stock over the same period (Armelius et al., 2022). Overall, as a near-cashless society, Norway provides an especially suitable setting for assessing household spending based on electronic transactions.

Our Consumption Measure and Comparison with the National Accounts Following the cleaning procedures explained above, in this paper we measure consumption by electronic transactions, after removing single wire transfers above 100,000 NOK2015, transfers who lack both COICOP and location information, and all transfers to banks (except imputed payments of credit card bills).

As a benchmarking exercise we now compare our spending measure with the official measure of nominal household consumption in the national accounts. We consider both Norwegian households' domestic (inside Norway) and total (domestic and abroad) consumption in the national accounts, in each case removing imputed housing consumption.[17]

In Figure 3a we plot the growth rates of our aggregated spending measure and household domestic consumption in the national accounts. Overall, the two series track each other well, with a correlation of 0.83 over the sample period.[18] In Figure 3b we plot the same series in per-capita terms,[19], showing a similar pattern (the correlation is 0.81). Hence, although the definition and measurement of consumption in the national accounts differs from our expenditure measure, reassuringly they appear highly correlated.[20] In Figure B2 we plot the growth series for the broader national accounts consumption measure, which includes consumption abroad. Table B3 contains a summary of the comovements.

2.2 Administrative Data

We combine our electronic expenditure data with administrative records containing detailed information on income, assets, demographic characteristics and labor market status, for the universe of Norwegian residents over the period 1993-2018.[21] The income and asset data are

[17] Both of these provide instructive benchmarks against our transactions-based measure of spending, which only partly captures transactions made abroad, through imputed credit card bills.

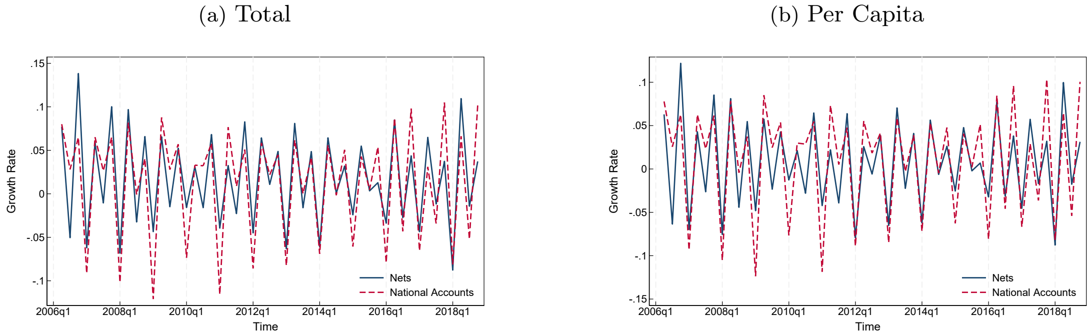
[18] In Appendix Figures B3a and B3b we plot the time series of the levels of both domestic and total national accounts consumption.

[19] For the national accounts measure we normalize by the population in Norway measured at a quarterly frequency. For the electronic expenditure measure we normalize by the quarterly measure of people observed with at least one electronic transaction

[20] The high correlation corroborates the findings in Aastveit et al. (2020), who find that debit card data outperform other time series when nowcasting household national accounts consumption in Norway.

[21] This dataset has been extensively used for research, and it is documented in detail in other papers (see for example, Fagereng et al. (2020) and Holm et al. (2021)).

Figure 3: Comparison with National Accounts (Growth).



Notes. This figure plots the quarterly growth rates of nominal household domestic consumption from the national accounts (dashed line) and aggregate household electronic expenditures (solid line). In panel (a) we use total amounts, while in panel (b) the national accounts is measured per-capita, and the electronic expenditures is measured per-user. For the electronic expenditure measure we remove single wire transfers above 100,000 NOK (12,500 USD2015), person-to-person transfers, and all transfers to banks, except imputed payments of credit card bills.

collected for tax purposes by the Norwegian Tax Authority, and for the most part they come from pre-filled tax declarations reported by third parties such as employers and banks. The data contain information on income (labor income, and capital income and expenses), total debt, financial assets (bank deposits and securities) and real wealth (e.g. housing wealth, cars and business wealth). Income and expense measures are yearly totals, while asset values are measured at the end of the year. We also observed demographic characteristics such as age, education and family relations, from which we construct households. The labor market data is based on information from an employer-employee registry containing information such as the industry and occupation of each employee. We also observe linked bank-person information, allowing us to observe households bank connections. We exploit this information in Section 4.

2.3 Sample Restrictions and Summary Statistics

Our unit of analysis it the household, defined as individuals in a family relation living at the same address. We implement several sample criteria to exclude observations where our electronic expenditure data may not accurately reflect consumption expenditures. First, we exclude households who report self-employment income on their tax returns. For these individuals it is difficult to separate between private and business expenditures. Second, we exclude household-years in which at least one family member migrates, as we are less likely to cover expenditures abroad. Third, we remove households with very few electronic transactions. In particular, we require that households in at least half of the months report a minimum of four debit card transaction and one wire transfer.

Our final sample consists of around 13 million household-year observations. Summary statistics are reported in Table 1. We deflate all nominal variables using the core consumer price index CPI-ATE constructed by Statistics Norway.[22]

2.4 Institutional details

The credit and housing markets in Norway provide an ideal setting to study the cash-flow effects of monetary policy. Compared to most other developed countries, Norway has a high rate of homeownership and a high debt-to-income ratio among households. Over our sample period $2006-2018$, household debt on average constituted 219% of disposable income in Norway. Over the same period, the median in a group of 36 mostly developed countries was 108%.[23] The homeownership rate in Norway was 77% on average between 2015 and 2018, and 85% of household debt consisted of mortgage debt.

The high prevalence of adjustable-rate loans makes Norway particularly well-suited for examining how monetary policy affects consumption in the short-run. Of all outstanding household loans, 91% have a floating interest rate, which is defined as a residual fixation period of less than 3 months. Similarly, 88% of bank deposits are short-term transaction deposits, allowing for flexible withdrawals and payments without significant costs.[24] The interest rate on adjustable-rate loans is generally set as a time-varying markup over the three-month Norwegian Interbank Offered Rate (NIBOR), which serves as the primary reference rate in the Norwegian market. By law, banks are required to give customers six weeks' notice before increasing lending rates and eight weeks' notice before decreasing deposit rates. They are not required to give notice when decreasing lending rates or increasing deposit rates. Estimations of pass-through effects based on panel data from $1991-2017$ by Juelsrud et al. (2020) indicate that around 80% of a policy rate change is reflected in average lending rates within one to two quarters. Our own estimations, using data from 2013 to 2018, suggest that approximately 50% of a policy rate change passes through to both lending and deposit rates within two quarters (see Section 3.1.3).

[22]The CPI adjusted for tax changes and excluding energy products, CPI-ATE, is a measurement of the underlying growth in consumer prices. We use the monthly index for consumption and the yearly one for income and balance sheet variables.

[23]OECD (2024), Household debt database, https://www.oecd.org/en/data/indicators/household-debt.html (accessed on December 6, 2024).

[24]Transaction deposits are deposits from which payments and withdrawals can be made without costs beyond regular transaction fees. Data for lending rates cover the period $2013-2018$, while data for deposit rates are from $2015-2018$, both from Statistics Norway.

Table 1: Sample Summary Statistics

	full sample	Decile of interest exposure									
		1	2	3	4	5	6	7	8	9	10
median age hh. head	45	65	56	42	47	48	48	45	42	39	36
median consumption/income	0.68	0.64	0.64	0.61	0.65	0.68	0.70	0.70	0.70	0.70	0.73
median debt/income	1.62	0.00	0.04	0.12	0.63	1.19	1.81	2.43	3.09	3.92	5.64
median deposits/income	0.21	2.22	0.64	0.10	0.16	0.19	0.18	0.15	0.13	0.11	0.11
median liquid assets/income	0.25	2.46	0.72	0.11	0.18	0.23	0.22	0.19	0.16	0.14	0.14
income after tax (2015 USD)	58,370	52,589	50,557	40,017	51,183	62,724	73,202	77,254	75,973	69,872	54,766
net worth (2015 USD)	91,724	408,193	203,854	3149	28,687	138,765	142,060	112,929	79,317	47,654	10,327
frac. single person hh.	0.42	0.49	0.48	0.56	0.45	0.38	0.32	0.29	0.30	0.35	0.49
frac. multi-person hh.	0.51	0.49	0.47	0.35	0.48	0.57	0.63	0.66	0.63	0.56	0.40
frac. with children in hh.	0.29	0.08	0.14	0.22	0.23	0.27	0.34	0.42	0.46	0.44	0.33
frac. head and spouse employed	0.61	0.34	0.48	0.51	0.58	0.62	0.66	0.70	0.73	0.74	0.70
frac. at least one employed	0.73	0.46	0.61	0.61	0.71	0.76	0.81	0.85	0.87	0.88	0.81
frac. homeowner	0.70	0.76	0.58	0.31	0.49	0.66	0.81	0.88	0.91	0.91	0.87
frac. higher education hh. head	0.32	0.29	0.26	0.18	0.26	0.32	0.34	0.34	0.36	0.39	0.43
observations (households-years)	13,342,546										

Notes. The table shows sample statistics for the final sample of households as well as by decile of interest exposure, defined as debt subtracted deposits and divided by income. Liquid assets are deposits, stocks and mutual funds. Higher education is education above high school level.

3 The Cash-flow Channel of Monetary Policy

We estimate how the consumption response to monetary policy depends on households' direct exposure to movements in short-term interest rates through debt and bank deposits, what's known as the cash-flow channel of monetary policy.[25] The fundamental identification problem we need to address is the endogeneity of monetary policy with respect to macroeconomic conditions. While monetary policy affects household consumption, it also reacts partly to other factors that drive consumption growth. For instance, a positive foreign demand shock increases output and consumption in the Norwegian economy, leading the central bank to increase the policy rate. Since the policy rate typically rises in response to an increase to shocks that drive up consumption, a projection of consumption growth on the change in interest rates would be biased towards zero.

In this section, we deal with this identification problem in two ways. In Section 3.1, we use time fixed effects to control for unobserved drivers of consumption growth that also affect the interest rate. This allows us to identify the differential effect of monetary policy on consumption between households that are expected to be exposed to a smaller or larger degree to changes in the interest rate based on their ex ante balance sheet composition. In Section 3.2, we instrument for changes to monetary policy using a new set of high-frequency instruments for Norway. This allows us to not only estimate the relative effect across households, but also the total effect of monetary policy on consumption. In Section 3.2.4, we demonstrate that the previous estimates, under specific assumptions, can be understood as marginal propensities to consume out of the cash-flow change triggered by monetary policy.

3.1 Identification With Fixed Effects

3.1.1 Empirical Strategy

We estimate how the consumption response to interest rate movements vary with households' ex ante exposure to monetary policy. Specifically, we estimate the local projection (see Jordà, 2005)

$$\frac{c_{i,t+h} - c_{i,t-1}}{y_{i,\text{year}_t-1}} = \beta^h \Delta r_t \times \text{EXP}_{i,t} + \delta_i^h + \xi_t^h + \sum_{n=1}^{N} \gamma_{t,k}^{h,n} + X_{i,t}\alpha^h + \epsilon_{i,t}^h \tag{1}$$

separately for every horizon h, the number of months since the interest rate change Δr_t. The coefficient β^h measures how the effect of monetary policy on consumption varies with households' ex ante interest exposure $EXP_{i,t} = \frac{b_{i,\text{year}_t-1} - d_{i,\text{year}_t-1}}{y_{i,\text{year}_t-1}}$, where both debt b and bank deposits d

[25] See e.g. Flodén et al. (2020).

are measured at the end of the year previous to period t. As such, exposure is a pre-determined variable, but a single household can be part of different exposure groups at different points in time.[26]

Because our underlying consumption data is measured at a weekly frequency and the weeks do not line up exactly with calendar months, our dependent variable uses a three-month rolling average of consumption. Specifically, the variable $c_{i,t}$ is the average of the consumption of household i in the 12 weeks centered on month t.[27] Furthermore, y_{i,year_t-1} is the household's income in the previous year. We normalize the dependent variable by income in order to later compare our results to direct estimates of the marginal propensity to consume, as explained in Section 3.2.4.[28]

We include multiple levels of fixed effects to control for endogeneity of monetary policy. In equation 1, the household fixed effects δ_i^h account for the differences in average consumption growth between households. The time fixed effects ξ_t^h account for variation in consumption growth between months that is common to all households. In addition, we include several fixed effects $\gamma_{t,k}^{h,n}$ that are interactions between the time fixed effects and a pre-determined household observable, indexed by n. In our benchmark specification, we include $N = 9$ levels of these fixed effects: county of residence, age of household head, employment dummies for both household head and partner, industry of employment for the household head, the number of people in the household, a homeowner dummy, and deciles for each of household income, wealth/income and liquid wealth/income.[29]

Including these fixed effects serves three purposes. First, by accounting for some of the variation in the household consumption growth, they reduce the variance of the error term $\epsilon_{i,t}^h$ and thereby potentially reduce the size of the standard errors. Second, and more importantly, they can remove the component of the error term that is correlated with the interest rate change Δr_t. The OLS estimator of β^h is consistent if changes in the policy rate are correlated with unobserved drivers of consumption growth that are common to households within the groups that the fixed effects account for. For instance, the central bank could partly set the interest rate based on employment growth that varies between regions (accounted for by time-county fixed

[26]We exclude observations with either values of the dependent variable or values of $EXP_{i,t}$ above the 99th and below the first percentiles.

[27]Since income is a yearly variable, we multiply the consumption variable by 400. Then, an increase in the dependent variable of 1 unit can be interpreted as an increase in consumption corresponding to 1 percent of income.

[28]This specification of the dependent variable is also the one used by Holm et al. (2021).

[29]We also include a set of time-month fixed effects that account for variation in the interest rate that correlates with the calendar month.

effects), or based on shocks to income growth that affect consumption equally within age cohorts (accounted for by time-age fixed effects). Furthermore, the fixed effects control for other ways in which monetary policy may differentially affect households in ways that systematically covary with interest exposure. For instance, highly indebted households might also be more likely to lose their job when aggregate demand drops, which might result in a large drop in expenditures. To the extent that the observable characteristics that we interact with time fixed effects capture the likelihood of unemployment, we control for this confounding effect. Hence, including the fixed effects allow us to credibly separate the cash-flow channel from other transmission channels of monetary policy.

We also include a vector of household control variables $X_{i,t}$. This vector includes the exposure variable and the lagged dependent variable.[30] We also include 12 month dummies as well as interacting these dummies with the exposure variable. Since the regression is by horizon h, the effects of all controls on the dependent variable are allowed to vary flexibly by horizon. The error term $\epsilon_{i,t}^{h}$ is specific to a household, month and horizon. We cluster standard errors by time and household.[31]

We use the 3 month money market rate (the Norwegian Interbank Offered Rate, NIBOR) as our measure of r_t. NIBOR is the reference rate used by Norwegian banks when setting their lending and deposit rates. It also closely follows the main policy rate set by Norges Bank. Figure E5 shows that all these rates track each other over time, but with different levels.[32]

3.1.2 Net Interest Exposure

Figure 4 plots the estimates for β^h in regression 1 by horizon (month) h. It shows the differential response to a 1 percentage point increase in the money market rate between households with high and low interest exposure. In Figure 4a, we show the estimates of the specification with only time fixed effects. In Figure 4b, we include the full set of fixed effects. The two specifications give similar results.

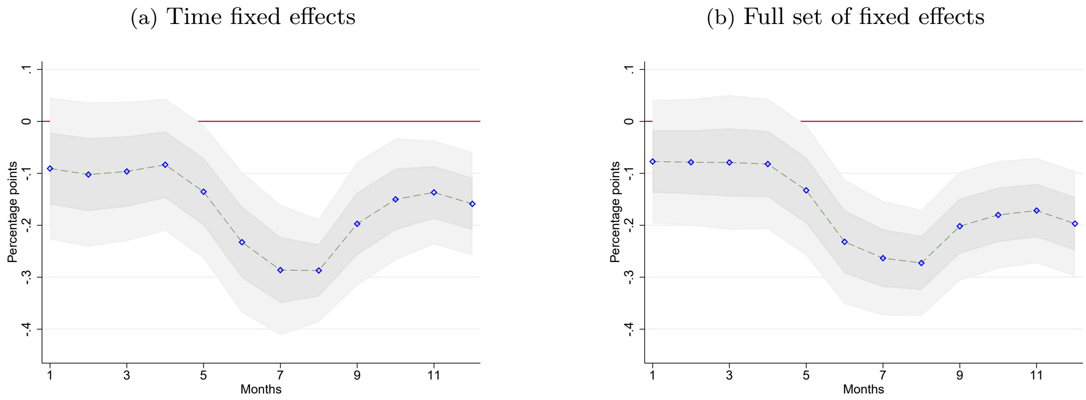
The interpretation of the point estimate -0.077 for the first month is that the median house-

[30] All balance sheet variables used for controls are measured at the end of the year before period t. The lagged dependent variable is defined as $\frac{c_{i,t-2}-c_{i,t-5}}{y_{i,\text{year}_t-1}}$.

[31] It is computationally too costly to run regression 1 on the full panel of Norwegian households for all years and months. For that reason, we have estimated the regression on a 15% random sample of households. We sample randomly from the full list of identifiers of households that are in our dataset in at least one year between 2006 and 2018. If a household is sampled, it stays in our sample for all years it is present. We have done the sampling two times and checked that the results do not change across samples.

[32] While the lending and deposit rates are more directly related to the cash-flow changes experienced by households, these rates are only available at a monthly frequency starting in December 2013.

Figure 4: Relative Consumption Response to Interest Rate Hike.



Notes. The figures show the estimates of coefficient β^h from regression 1 for horizons (months) $1-12$. This coefficient can be interpreted as the additional response in consumption to a 1 percentage point higher interest rate when ex ante interest exposure is 100 percent higher. The figure on the left-hand side shows the estimates for the regression that only includes time fixed effects, while the right-hand side figure shows the estimates for the regression with a full set of time-household fixed effects.

hold, which has an exposure equal to 1.25, reduces consumption by 0.097 (0.077 times 1.25) percentage points more, as a fraction of income, than a household with zero exposure if the interest rate increases by 1 percentage point. Our estimates indicate that the differential response increases starting around month 5 and reaches a peak in month 8. In month 6, the median household reduces consumption by 0.29 percentage points more (0.23 times 1.25), and households at the 90th percentile by 1.01 percentage points more, than a household with zero exposure. Except for the first few months, the estimates are statistically significant at the 5 percent level.

Combining our coefficient estimates with the median consumption-to-income ratio of 0.68 (see Table 1), a back-of-the-envelope calculation indicates that consumption falls by approximately 0.4 percentage points more ($\frac{0.23\times1.25}{0.68}$) after 6 months for the median household, and 1.5 percentage points more for a household at the 90th percentile, compared to the not-exposed households. Our estimates are slightly smaller than the comparable results for Swedish data from Flodén et al. (2020).

3.1.3 Debt and Deposits

So far, we have assumed that the consumption response to interest rate changes depends on net exposure, defined as the difference between gross debt and deposits. To investigate the separate

Table 2: Estimated consumption responses

	Regression 1	Regression 2		Regression 3			
	Exposure (β^h)	Deposits (β^h_d)	Debt (β^h_b)	Deposits (β^h_d)	Debt, bottom tertile liquid ($\beta^h_{b,1}$)	Debt, middle tertile liquid ($\beta^h_{b,2}$)	Debt, top tertile liquid ($\beta^h_{b,3}$)
Month 1	-0.077^*	0.150	-0.072^*	0.096	-0.105	-0.083^*	-0.001
	(0.060)	(0.156)	(0.050)	(0.146)	(0.119)	(0.044)	(0.066)
Month 2	-0.079^*	0.117	-0.080^*	0.069	-0.087	-0.116^{**}	-0.014
	(0.061)	(0.155)	(0.051)	(0.149)	(0.116)	(0.052)	(0.062)
Month 3	-0.079^*	-0.062	0.129^{**}	-0.119	-0.134^*	-0.176^{***}	-0.050
	(0.066)	(0.150)	(0.053)	(0.162)	(0.123)	(0.057)	(0.062)
Month 4	-0.082^*	-0.135	-0.143^{**}	-0.218^*	-0.182^*	-0.174^{**}	-0.031
	(0.063)	(0.144)	(0.048)	(0.146)	(0.119)	(0.060)	(0.062)
Month 5	-0.133^{**}	-0.100	-0.192^{***}	-0.228^*	-0.309^{**}	-0.178^{**}	-0.016
	(0.063)	(0.153)	(0.048)	(0.152)	(0.106)	(0.066)	(0.056)
Month 6	-0.232^{***}	0.211^*	-0.244^{***}	0.078	-0.374^{***}	-0.217^{**}	-0.061
	(0.061)	(0.198)	(0.050)	(0.195)	(0.100)	(0.073)	(0.064)
Month 7	-0.263^{***}	0.375^{**}	-0.251^{***}	0.260^*	-0.339^{***}	-0.257^{***}	-0.098^*
	(0.056)	(0.182)	(0.051)	(0.195)	(0.087)	(0.078)	(0.069)
Month 8	-0.273^{***}	0.450^{***}	-0.247^{***}	0.409^{**}	-0.222^{**}	-0.292^{***}	-0.205^{**}
	(0.052)	(0.136)	(0.056)	(0.151)	(0.095)	(0.077)	(0.065)
Month 9	-0.203^{***}	0.316^{**}	-0.175^{**}	0.319^{**}	-0.090^*	-0.248^{**}	-0.187^{***}
	(0.053)	(0.125)	(0.065)	(0.108)	(0.089)	(0.095)	(0.059)
Month 10	-0.180^{***}	0.202^*	-0.167^{**}	0.215^{**}	-0.091^*	-0.220^{**}	-0.185^{**}
	(0.052)	(0.127)	(0.061)	(0.102)	(0.063)	(0.102)	(0.067)
Month 11	-0.172^{***}	0.225^*	-0.153^{**}	0.233^{**}	-0.120^*	-0.159^*	-0.160^*
	(0.051)	(0.124)	(0.055)	(0.102)	(0.065)	(0.106)	(0.082)
Month 12	-0.197^{***}	0.185^*	-0.190^{***}	0.192^*	-0.184^{**}	-0.167^*	-0.184^*
	(0.051)	(0.134)	(0.052)	(0.113)	(0.090)	(0.104)	(0.095)

Notes. The table shows results of the regressions in Section 3.1. Each row shows the coefficient estimates and standard errors for a particular month (horizon). Standard errors are clustered by household and time.

role each of these components play for transmission, we estimate

$$\frac{c_{i,t+h} - c_{i,t-1}}{y_{i,\text{year}_t-1}} = \beta^h_b \Delta r_t \times \frac{b_{i,\text{year}_t-1}}{y_{i,\text{year}_t-1}} + \beta^h_d \Delta r_t \times \frac{d_{i,\text{year}_t-1}}{y_{i,\text{year}_t-1}} + \delta^h_i + \xi^h_t + \sum_{n=1}^{N} \gamma^{h,n}_{t,k} + X_{i,t}\alpha^h + \epsilon^h_{i,t}, \quad (2)$$

where β^h_b is now the coefficient on debt and β^h_d the coefficient on deposits. In Section 3.1.1, we implicitly assumed that the consumption response to a given change in the interest rate only depends on *net* debt, now how it is distributed across gross debt and deposits. In that case, $\beta^h_b = -\beta^h_d$.

In Table 2, the second column replicates the benchmark estimates of β^h from equation 1 for months $1-12$, while the columns $3-4$ shows the results when splitting the regressor into separate terms for deposits and gross debt, respectively, as in equation 2. In all cases we include a full set of fixed effects as well as other control variables.

The estimates of β^h_b are similar to the estimates of β^h from the benchmark specification, indicating that the consumption responses are the same whether we consider variation in net debt or gross debt holding the level of deposits fixed. The estimates for β_d^h, on the other hand, show that holding gross debt fixed, there is no clear relationship between deposits and the consumption response to an interest rate change within the first half year or so. In the second half of the year, the point estimates of β_d^h average to 0.33, which is slightly higher than the the average of the estimates for $-\beta_b^h$ of 0.24, but the former are only statistically different from zero at the 5% level in months $7-9$.

Why is the cash-flow effect through households' deposits slower than the cash-flow effect through gross debt, holding fixed other observables? This difference can be due either to a slower pass-through of changes in the policy rate to deposit rates than to lending rates, or it can be due to a lower marginal propensity to consume out of the interest earnings on deposits. To investigate this, we estimate pass-through regressions by projecting separately the average monthly lending rate and the average monthly deposit rate at various horizons on the initial change in the money market rates.[33] The results are shown in Figure E8. The lending and deposit rates exhibit very similar dynamics following an increase in the money market rate. They both peak at an increase of around 1 percentage point after one year. While not conclusive, this points in the direction of a different consumption response to a change in the deposit rate than to the same change in the lending rate.

3.1.4 Liquid Assets

Deposits matter for a household's response to a change in monetary policy because they matter for the size of the cash-flow change. But a large literature has found that deposits, or more generally liquid assets, also affect the marginal propensity to consume out of any temporary change in disposable income. In HANK models, agents are subject to borrowing constraints and can hold both liquid and illiquid assets. If the stock of illiquid assets are subject to adjustment costs, agents with low levels of liquid assets relative to income have a high MPC regardless of their net worth (Kaplan et al., 2018). In response to a temporary shock that lowers their disposable income, these agents adjust their consumption in the short run instead of drawing down their stock of illiquid assets.

We test whether the cash-flow effects of monetary policy on consumption are stronger for less

[33] The regression we estimate is $r^{hh}_{t+h} = \alpha_0^h + \alpha_1^h r^{hh}_{t-1} + \alpha_2^h \Delta r_t + \varepsilon_t^h$, where r^{hh}_{t+h} is either the lending or deposit rate at horizon $t+h$ and Δr_t is the change in the money market rate between month $t-1$ and month t. We use the interest rates on all outstanding repayment loans and on deposits for the household sector, both from a sample of banks and mortgage companies and made available by Statistics Norway. These rates are only available starting in December 2013. Hence the pass-through estimates are based on less than half of the years in our sample, and the results should be interpreted with caution.

liquid households by estimating

$$\frac{c_{i,t+h} - c_{i,t-1}}{y_{i,\text{year}_t-1}} = \sum_{l=1}^{3} \beta_{b,l}^{h} \Delta r_t \times \frac{b_{i,\text{year}_t-1}}{y_{i,\text{year}_t-1}} \times \mathbb{I}_{l,i,t} + \beta_d^h \Delta r_t \times \frac{d_{i,\text{year}_t-1}}{y_{i,\text{year}_t-1}} + \delta_i^h + \xi_t^h + \sum_{n=1}^{N} \gamma_{t,k}^{h,n} + X_{i,t}\alpha^h + \epsilon_{i,t}^h, \quad (3)$$

where $l = 1$ is the first tertile, $l = 2$ is the second tertile and $l = 3$ the third tertile of liquid assets. $\mathbb{I}_{l,i,t}$ is an indicator function for whether household i is in tertile l based on its liquid assets relative to income at the end of year $\text{year}_t - 1$. Following Holm et al. (2021), we define liquid assets as the sum of bank deposits, government and corporate bonds, publicly traded stocks and mutual fund shares.

The estimates from regression 3 are shown in columns 5−8 of Table 2. On average throughout the 12 months following an interest rate change, given the level of debt-to-income, consumption responds more strongly for less liquid households. In particular, in the first few months following an increase in the interest rate, households with more debt reduce their consumption more than those with less debt only if they are not in the top tertile of liquid assets relative to income. However, towards the end of the year, highly liquid households have similar consumption sensitivity as those with less liquidity.[34] Hence, while the average dynamic consumption response in Figure 4 is initially driven by less liquid households, over time liquidity does not seem to matter for the consumption response.

That liquidity does seem to matter on average is consistent with the theory developed by Kaplan and Violante (2014) and in the subsequent HANK literature. It is also consistent with other empirical studies. Notably, using annual micro-data for Norway, Holm et al. (2021) find that those with low liquid assets relative to income react more strongly to an interest rate shock. Yet, the similarities we find between households with high and low liquidity at the end of the year are in line with a growing body of empirical evidence documenting high consumption sensitivity also among highly liquid households (Parker et al., 2013; Kueng, 2018; Olafsson and Pagel, 2018; Ganong et al., 2020; Fagereng et al., 2021; Lewis et al., 2024; Andre et al., 2024). [35]

[34] For annuity loans, which are common in Norway, principal payments are automatically increased (decreased) in the short run when the floating interest rate on the loan is decreased (increased). As a result, borrowers who do not make any adjustments to their principal payments experience a smaller change in their cash-flow in the short run than what is implied by the change in interest payments. When the borrowing rate increases, this mechanism can potentially help low liquidity constrained households avoid cutting consumption as much as they otherwise would, by automatically freeing up cash from lower principal payments.

[35] Andre et al. (2024) and Ilut and Valchev (2023) build models with near-rational agents consistent with such behavior of unconstrained agents.

3.2 Identification With Monetary Policy Instruments

In Section 3.1, we dealt with the endogeneity of monetary policy by including a rich set of fixed effects. In this section, we instead instrument the interest rate change with high-frequency monetary policy instruments. Using the instruments allow us to identify not only the heterogeneity in consumption responses between households, but also the total effect on consumption, since we can avoid including time fixed effects in the regression.

3.2.1 Empirical Strategy

We order households into quantiles of their interest exposure and estimate how much the response of consumption to a change in the interest rate varies over time and across the quantiles. Specifically, we estimate the local projection

$$\frac{c_{i,t+h} - c_{i,t-1}}{y_{i,\text{year}_t-1}} = \beta_g^h \Delta r_t + \delta_i^h + X_{i,t}\alpha_g^h + \epsilon_{i,t}^h \quad \forall i \in \mathcal{I}_g \tag{4}$$

for every horizon h and every group of households $\mathcal{I}_g$ separately. The groups are specified below. We include in the vector $X_{i,t}$ household income in the previous year, total wealth relative to income, liquid wealth relative to income, and the lagged dependent variable. We also include 12 month dummies and a second order polynomial in time. Since the regression is by horizon h, the effects of all controls on the dependent variable are allowed to vary flexibly by horizon.

The coefficient β_g^h now identifies the average effect within group $\mathcal{I}_g$ of a one percentage point increase in the interest rate on consumption after h months, measured in units of income. The construction of the groups is explained below.

3.2.2 Identification of Monetary Policy Instruments

We construct a new set of monetary policy instruments for Norway based on high-frequency changes in market expectations on announcement days. When Δr_t is instrumented, regression 4 is a local projection instrumental variables (LP-IV) regression (Stock and Watson, 2018).

The construction of our monetary policy instruments follows a two-step procedure. First, following a large literature (see Gürkaynak et al. (2005), Gertler and Karadi (2015), and Jarociński and Karadi (2020), among others), we extract the surprise element of monetary policy announcements from high-frequency changes in market-based expectations on announcement days. The expectations are based on the pricing of four forward rate agreements (FRAs), which gives us a total of four instruments. These instruments reflect the change in the market's expectations of the 3 month money market rate in a 30 minute window around the announcement time, from 10 minutes before the announcement to 20 minutes after the announcement.[36] The shorter the window, the less we expect the expectations to be affected by other macroeconomic conditions that might also be correlated with consumption growth. At the same time, it is important to allow enough time for the market to process the monetary policy announcement.

Second, we adjust our instruments to account for the information effect of monetary policy decisions. As argued by Blinder et al. (2008), among others, central banks provide the public with information about the macroeconomic outlook as well as the outlook for their own decisions. Some of this information is transmitted on announcement days in the form of central bank forecasts for macroeconomic variables. This might invalidate the exclusion restriction of the instrument, for instance when a policy hike is a signal that the macroeconomic outlook is stronger than previously assumed by agents in the economy. We follow Miranda-Agrippino and Ricco (2021) in adjusting the market-based surprises for this information component. First, we project the surprises on a set of forecasts and forecast revisions for inflation and output growth prepared by Norges Bank ahead of each meeting of the Monetary Policy Committee. These forecasts might contain information about the state of the economy that have not already been internalized by agents in the economy. Second, we extract the residuals from this regression and project them on their own lags, thereby removing a potential autoregressive component of the surprises that can be due to slow absorption of information among market participants (Miranda-Agrippino and Ricco, 2021). The residuals from this second regression are our final instruments. See Appendix D for a detailed description of how the instruments are constructed.

3.2.3 Results

We first order the households into 20 *ventiles* – 5 percent groups – based on the interest exposure variable $EXP_{i,t}$ used in Section 3.1. Table 1 summarizes the sample characteristics of each of the exposure groups. The median interest exposure within each group increases from -2.0 in the first decile (bottom two ventiles) to 5.4 in the top decile (top two ventiles). We run regression 4 separately for each group and each horizon.[37]

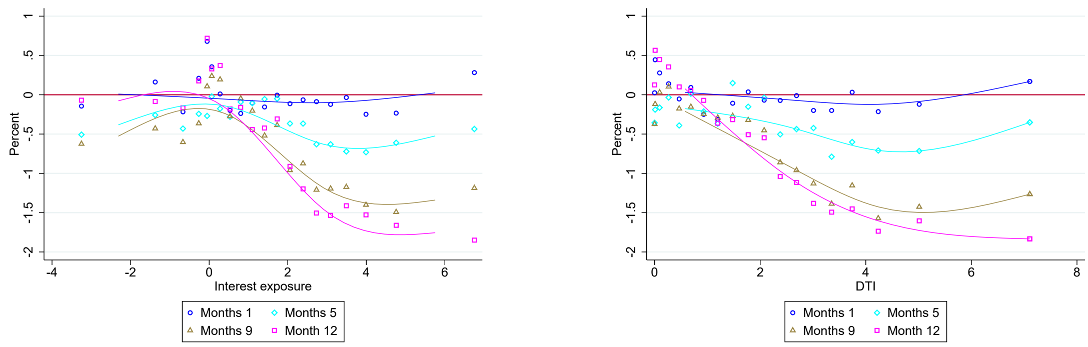
Appendix Figure E9 shows the effect of a one percentage point increase in the interest rate on consumption by interest exposure, for each month from 1 (impact) to 12. The results at four

[36]The same FRA contracts have previously been used by Brubakk et al. (2022) to generate monetary policy instruments for Norway.

[37]In Appendix E.1, we show that estimating the consumption response by group using OLS and fixed effects, as in Section 3.1, gives similar results as in this section.

Figure 5: Consumption Response to Interest Rate Hikes.

(a) By exposure (b) By debt/income



Notes. The figure shows the results from regression 4 by time horizon and quantiles (20 ventiles) of households based on interest exposure (panel (a)) and debt-to-income (panel (b)). Month 0 is the month of the instrumented interest rate change. Each dot is a separate estimate of coefficient β_g^h of the regression for a particular ventile g and horizon h. The median value of the grouping variable for each of the ventiles is shown on the horizontal axis. The vertical axis shows the estimated response of consumption, relative to its level in the three months before the change in the interest rate, in percent of income. To ease exposition, we fit a spline to the dots separately by horizon.

particular horizons – on impact and after 5, 9 and 12 months – are summarized in Figure 5a. To aid legibility, we add flexible splines fitted to the estimates for each of the horizons separately.[38] The point estimates indicate that there is no response in consumption on impact (month 1) for any of the groups, but by month 5 the consumption response is increasing in interest exposure, with a negative response of around 0.7 percent of income at the top of the distribution. This number rises to around 1.7 percent after one year.

For households with more debt than bank deposits, the consumption response is near linear in interest exposure. If anything, the slope of the consumption response with respect to interest exposure is lower at the very top of the distribution – within the top 20 percent – than for households with moderate exposure. For households with more bank deposits than debt, the consumption response does not vary with exposure. In fact, these households do not appear to respond to the interest rate changes at any horizon. As we see in Table 1, households with negative exposure typically have very little debt. Instead, decreasing exposure is associated mostly with increasing deposits for these households.[39] For households with positive interest exposure,

[38] As in Section 3.1, we cluster standard errors by both households and time. With these standard errors, the estimated consumption responses are not significant at the 5% level. Clustering by only time results in responses that are statistically significant at the 5 percent level. In Appendix E.1, we show that estimating consumption responses by group using OLS and fixed effects gives responses that are of a similar magnitude, but also statistically significant for most groups and horizons even with the conservative standard errors.

[39] Households with negative exposure are also older and less likely to be employed than households with positive exposure. In the OLS regression described in Appendix E.1, we control for time-age and time-employment fixed effects. There we find evidence of a slope in the coefficients with respect to exposure also for the groups with negative exposure.

increasing exposure is mostly associated with increasing levels of debt, as these households on average hold little deposits.

To further investigate the separate role of deposits and debt, we now order the households by their debt-to-income (DTI) ratio and rerun regression 4. The results for a subset of horizons are shown in Figure 5b.[40] The consumption response is close to linear in DTI across the full distribution. Hence, as in Section 3.1.3, our estimates point to stronger cash-flow effects through debt than through deposits.

Our results are most closely related to the work by Holm et al. (2021). Using consumption imputed from annual tax returns in Norway over the period $1993 - 2018$, they estimate the response to a narrative interest rate shock by decile of net interest exposure.[41] At the $0 - 1$ year horizon, they find a similar slope of the consumption response with respect to exposure as us. The estimated response is close to zero for households with debt net of deposits between the 20th and the 60th percentile, and – reflecting our estimates in the second half of the year – they find that the difference in consumption response between the 10th and 90th percentile is around 1.5 percentage points. Unlike us, they find that households in the bottom decile (who have more deposits than debt) increase their consumption in response to an increase in the policy rate.

We can also compare the estimates from regression 4 to the *relative* consumption responses estimated in section 3.1. To get an equivalent measure from our IV results as our OLS results, we estimate a linear regression on the individual point estimates β_g^h from equation 4 (plotted in figure E9) for a particular horizon h. The slope of the line with respect to interest exposure can then be compared to the estimates for β^h from equation 1. In Figure 6 we see that the estimates have a similar magnitude and increase at a similar rate over time.

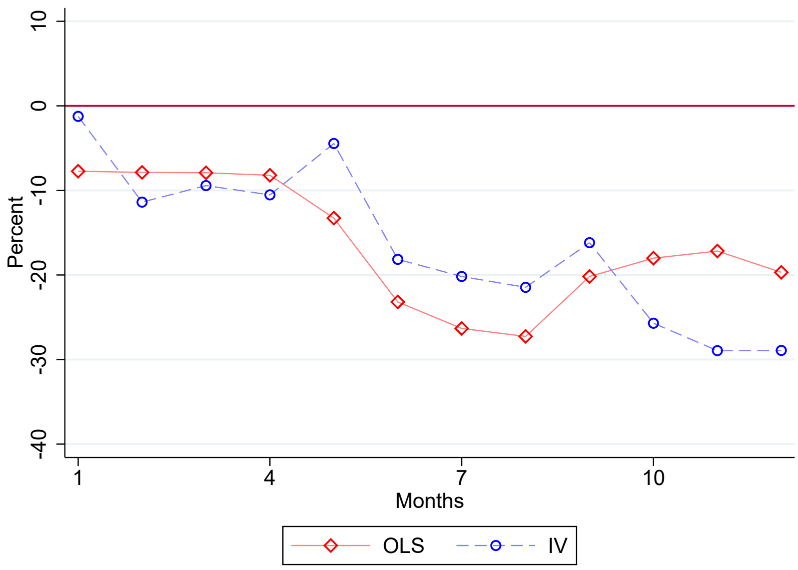
3.2.4 The Marginal Propensity to Consume

What is the marginal propensity to consume out of net interest expenses? To answer this question, we need to know not only the household consumption response, but also the cash-flow change induced by a change in monetary policy. Assuming homogeneous rates of pass-through to all households in the range estimated in section 3.1.3 and by Juelsrud et al. (2020), and assuming that net interest exposure in the year prior to the interest rate shock accurately captures the balance sheet position of the household that is affected by movements in the lending and deposit rates, a back-of-the-envelope calculation based on the estimated consumption responses from

[40] The full set of results are shown in Appendix Figure E10.

[41] Holm et al. (2021) define net interest exposure as the negative of our measure of exposure.

Figure 6: Cash-Flow Effects of Monetary Policy



Notes. The figure shows the point estimates from regression 1 (OLS) and equivalent estimates based on regression 4 (IV), by horizon (month) after a change in the interest rate. The blue dots are the estimated coefficients $\hat{\gamma}_1^h$ from the regression $\hat{\beta}_g^h = \gamma_0^h + \gamma_1^h \text{EXP}_g + \varepsilon_g^h$, separately estimated for each horizon h across groups g, where $\hat{\beta}_g^h$ is the estimated coefficient from regression 4 and EXP_g is the median net interest exposure within exposure group g.

section 3 gives an average yearly MPC in the range $0.185 - 0.38$.[42] In the next section we provide an alternative identification of the MPC out of interest expenses.

4 Household-specific Mortgage Rates: A Natural Experiment

In section 3, we employed time-variation in interest rates along with cross-sectional dispersion in household interest exposure to estimate the cash-flow channel of monetary policy. In this section, we directly measure cross-sectional variation in interest payments arising from a natural experiment. The differential movements in lending rates across households allow us to estimate the MPC out of interest payments more directly than in the previous section. We begin by

[42]To get to these numbers, we first assume that the MPC at horizon h is given by $\frac{\hat{\beta}^h}{\hat{\alpha}^h}$, where $\hat{\beta}^h$ is the estimated consumption response reported in figure 6 and $\hat{\alpha}^h$ is an estimate of the pass-through of a 1 percentage point increase in the short-run money market rate to lending and deposit rates at horizon h. We find that $\hat{\beta}^h$ is around 0.1 in the first two quarters and $0.2 - 0.3$ in the last two quarters of the year. Our own pass-through estimates, reported in figure E8, find a pass-through to both lending and deposit rates of around 0.3 on average within the first two quarters and 0.7 in the last two quarters. Using data over a longer time time, Juelsrud et al. (2020) find equivalent pass-through estimates of 0.8 and close to 1, respectively, at these horizons. Hence, the MPC is in the range $0.17 - 0.33$ in Q1-Q2 and $0.20 - 0.43$ in Q3-Q4. These numbers average to $0.185 - 0.38$.

describing the institutional background and the policy change, followed by an explanation of the sample selection and identification strategy, before we move on to the results.

4.1 Institutional Background

Since the early 1900s, Norway has operated a government-owned lending institution called Statens Pensjonskasse (SPK), which provides floating-rate-only mortgages to public sector workers at favorable rates.[43] Historically, the mortgage rate, which is universal and non-negotiable, was a markup over 3-month treasury bills. SPK mortgages were subject to a borrowing limit of 1,700,000 NOK (roughly 200,000 USD 2015) per individual and a loan-to-value cap of 80 percent.[44] In contrast, following the deregulation of the Norwegian banking sector in the 1980s, mortgage rates in conventional private sector banks were determined as a markup over the 3-month money market rate. Unlike the markup in conventional banks, which is an equilibrium object influenced by market demand and bank competition, the markup in SPK was set annually by the government as part of the National Budget. Historically, the SPK markup has been fixed at 50 basis points, resulting in the SPK borrowing rate being the best mortgage rate offer in the market and about one percentage point lower than the average bank mortgage rate.[45]

In the aftermath of the Great Financial Crisis (GFC), a structural shift materialized, causing the SPK spread to increase well above historical levels, as shown in Figure 7.[46] In the fall of 2013, as part of the 2014 National Budget process, the government decided to address this by raising the SPK markup by 75 basis points, effective from March 1st, 2014. The policy shift was not communicated to the public before the National Budget was published on October 8 2013, and it was credibly unrelated to other factors affecting the relative consumption growth between SPK customers and customers of other banks. The increased markup resulted in a rate hike which was communicated by letter to SPK customers in January 2014. This action was repeated in the 2015 budget process, resulting in a further 50 basis point increase in March 2015. Subsequently, in the 2016 National Budget, the government opted to introduce a completely new pricing formula, which remains in effect to this day. Under this formula, the SPK rate is set at

[43] In addition to offering mortgages to its members, SPK also operates an occupational pension scheme. It is not, however, a deposit taking institution.

[44] For many households this borrowing limit has been binding. Among SPK customers, 25 percent total debt is from other banks.

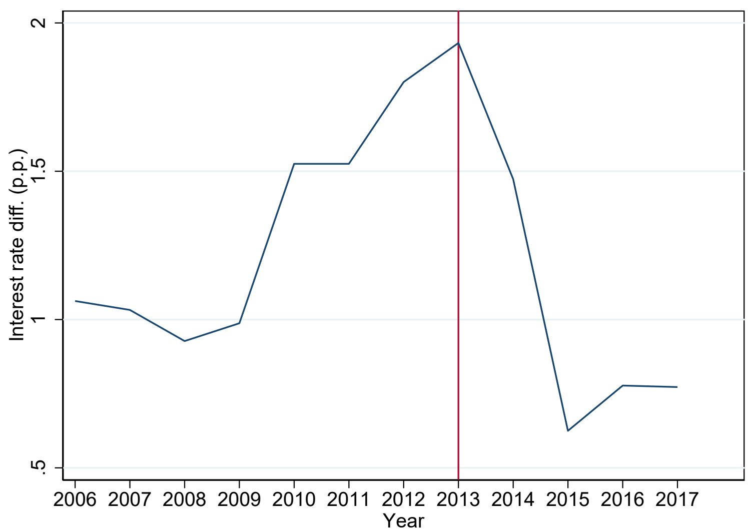
[45] Because of the way SPK set interest rates, the effective fixed-rate period was approximately 4 months, whereas in conventional banks the corresponding lock-in period was 6 weeks. During periods of rapidly declining rates, this meant that the SPK spread could temporarily become negative.

[46] The exact reason for this increase is unclear, but it likely stemmed from a combination of factors including a widened spread between treasury bills and money market rates, as well as reduced competitive pressure in the banking sector.

15 basis points below the average of the five best mortgage offers available in the market at any given time.

As a result of the series of policy reforms initiated in 2014, there was a substantial and rapid decrease in the interest differential, ultimately restoring the spread to its pre-GFC level by 2016, as shown in Figure 7. Our empirical strategy, outlined below, leverages the 2014 policy change as a starting point and compares the trajectory of interest expenses and consumption between SPK and non-SPK customers.[47]

Figure 7: Interest Rate Differential



Notes. This figure plots the percentage point difference in loan rates between all household debt and SPK mortgages. The rates are loan-weighted average of existing household level debt, assembled by Statistics Norway.

4.2 Sample Definitions and Descriptive Statistics

We conduct the analysis in this section at the yearly frequency in order to directly observe changes in household interest expenses. We label a household as an SPK customer if it had an outstanding stock of debt in SPK on December 31 2013, identifying 66,230 households as SPK customers at the end of 2013. We remove from our sample households that (i) are not customers of SPK either the year before or the year after 2013, and (ii) do not display a stable

[47]Since the interest rate differential is positive and time-varying even before 2013 (see Figure 7), there will likely be differences in consumption dynamics between the two groups that are driven by these mortgage rate movements even in the earlier years of our sample. We choose to focus on the years immediately after 2013 since the drivers of the interest rate differential in those years are clearly understood and exogenous to unobserved drivers of consumption.

Table 3: Summary Statistics, Treated and Control Group Households

	Control	Treated
median age hh. head	46	48
median consumption/income	0.67	0.67
median debt/income	2.85	2.52
share debt in SPK (median)	0.00	0.74
median deposits/income	0.21	0.30
median liquid assets/income	0.25	0.36
income after tax, per adult	43,848	51,264
net wealth, per adult	96,191	157,363
frac. multi-person hh.	0.69	0.82
frac. with children in hh.	0.37	0.47
frac. homeowner	0.91	0.98
observations (households)	328,104	22,393

Notes. The table shows pre-reform sample statistics for treated and non-treated households in Section 4. Income and net wealth are in 2015 USD. Liquid assets are deposits, stocks and mutual funds.

debt repayment trajectory in the two year period from December 31 2012 to December 31 2014.[48] The purpose is to remove households with large changes in interest payments to SPK between 2013 and 2014 driven by events unrelated to the rate hike in SPK, for instance housing market transactions or labor market moves in and out of the public sector.[49] After imposing restriction (i) and (ii) we are left with $22,393$ unique SPK households. These are the treated households. Of the households we lose, the majority (90 percent) is due to extensive margin debt movements in and out of SPK over the 2 year period. In the control group, we include households that display a stable debt repayment trajectory in their main bank, defined as the bank that holds the largest share of the household's debt, and who are not customers of SPK. The control group consists of $332,870$ unique households. In addition to the stable debt trajectories, we further impose the same type of sample restrictions as in Section 3 on both treated and control households.

Table 3 provides summary statistics for households in both groups pre-reform. Treated and control households are similar along most characteristics, though treated households have slightly higher income and net worth per adult, as well as more liquid assets relative to income. The treated group also consist of a slightly higher fraction of households with more than one adult and with children. We control for these characteristics and others in the regression below.

[48]A stable trajectory is defined as SPK debt declining each year, but with an annual re-payment below 10 percent of the beginning-of-year stock of debt.

[49]A potential concern arising from this restriction could be that a large share of SPK clients switched to other banks because of the 2014 reform. However, the SPK rate remained the best possible mortgage rate also after the reform, which mitigates this concern. In addition, the exit rate from SPK is stable at 5 percent each year between 2010-2014

4.3 Empirical Strategy

We estimate the regression

$$Y_{i,t} - \overline{Y}_i = \alpha_Y^t + \beta_Y^t D_i + X_i \gamma_Y^t + \epsilon_{i,t}, \tag{5}$$

where $Y_{i,t}$ is the outcome variable of interest (consumption or gross interest expenses) and $\overline{Y}_i$ is the value of this variable for household i in the reference year 2013, while $D_i \in \{0, 1\}$ is a dummy variable indicating whether household i is in the treated group. We run this regression separately for every year t.

We include a rich set of controls in the regression. The constant α_Y^t captures time variation in average consumption. The vector X_i includes a large set of pre-determined household control variables that might account for variation in household consumption and interest payments. We include 10 year age groups of the household head, dummy variables for the number of adults and the number of children in the household, the maximum education level for the household head and spouse (four levels), and dummy variables for the decile of the level of debt, the level of income and the level of consumption relative to income in 2012.

We estimate regression 5 separately by year and by outcome variables interest expenses and consumption, using 2013 as the reference year. The coefficient β_Y^t measures the difference in the outcome variable in year t between SPK and non-SPK households, controlling for other observables. Our estimate of the MPC out of interest expenses in year t is given by $-\frac{\beta^t_{\text{consumption}}}{\beta^t_{\text{interest exp.}}}$. Standard errors of the MPC estimates are bootstrapped with 200 draws.

4.4 Results

The estimates for regression 5 are shown in Table 4. All else equal, the average interest expenses of an SPK household increase by \$912 relative to a non-SPK household in 2014, while consumption falls by \$278 more in the former group. As a result, our estimated MPC out of interest expenses is 30.5 percent in 2014. All our estimates are significant at the 5 percent level.

In the second and third columns of Table 4 we report the same estimates for the years 2015 and 2016 relative to the reference year. The effect of treatment on interest expenses is larger than in 2014, reflecting the fall in the interest rate differential between SPK and other banks throughout 2015 shown in Figure 7. The estimated marginal propensity to consume out of these interest expenses is somewhat larger in both 2015 and 2016, rising to around 40% in both years, but they are not significantly different from the 2014 estimate.

Table 4: MPC out of interest expenses.

	Year		
	2014	2015	2016
interest exp.	912^{***}	1985^{***}	2154^{***}
	(8.9)	(16.1)	(20.6)
consumption	-278^{**}	-825^{***}	-835^{***}
	(86.9)	(118)	(137)
MPC	30.5^{**}	41.5^{***}	38.8^{***}
	(11.1)	(6.62)	(7.48)
Observations	289,182	289,168	273,786

Notes. The table shows the estimated coefficient β^t in regression 5 for each of the years $t \in \{2014, 2015, 2016\}$ and for both interest expenses and consumption. The coefficient estimates measure the effect of treatment (SPK households vs. non-SPK households) on the outcome variables. The estimates for interest expenses and consumption are in USD at the 2015 exchange rate. The estimate for the MPC out of interest expenses is derived from the former estimates. Standard errors for the MPC (in parentheses) are bootstrapped using 200 draws.

These MPC estimates fall within the range of imputed MPCs reported in Section 3.2.4, despite the fact that movements in net interest expenses induced by the policy reform may have been perceived by households to be more permanent than those caused by typical changes in the central bank policy rate. As shown in Figure E7, the increase in market rates induced by a typical monetary policy shock in our setting subsides within one to two years, while the policy reforms would have been expected to be of a more permanent nature. However, the roll-out of the reform was staggered, inducing a gradual reduction in the implied mortgage rate subsidy ending in a new permanent pricing formula in 2016. It is therefore possible that the reforms were perceived by the public – and by affected households – as of a more permanent nature over time. This can potentially explain why the point estimates of the MPC are higher in 2015 and 2016 than in 2014.

Our estimates of the MPC out of changes in interest payments can be compared to the wider literature on consumption responses to income shocks. Our imputed (Section 3.2.4) and direct MPC estimates are in the range of $20 - 40\%$. These magnitudes are within the range of typical estimates in the literature of responses to income shocks of various degrees of persistence.[50] For example, Ganong et al. (2020) report an average MPC out of typical labor income shocks (instrumented using co-worker pay) of around 23 percent, while estimates of the MPC out of income shortfalls from unemployment typically range from 30 to 50 percent (Andersen et al., 2023;

[50] When computing MPCs we ignore that interest income (expenses) is taxed (deducted) at the capital gains tax rate, which was around 27 percent during our sample period. Typically these taxes affect cash-flows in June the year after the change in interest payments. Accounting for the tax adjustment would raise our range of MPC estimates to $25 - 55\%$.

Patterson, 2023; Fagereng et al., 2024).[51] Similar magnitudes are also found for the MPC out of windfall gains, such as lottery prizes (Fagereng et al., 2021; Golosov et al., 2024), randomized cash transfers (Boehm et al., 2024), and tax rebates (Parker et al., 2013; Jappelli and Pistaferri, 2014; Misra and Surico, 2014; R. Baker et al., 2023; Borusyak et al., 2024; Orchard et al., 2024). Hence, our estimates indicate that the MPC out of net interest expenses is similar in size to the MPC out of other sources of disposable income fluctuations.

5 Conclusion

By estimating the short-run response of consumption to interest rate changes, this paper provides insights into the cash-flow channel of monetary policy and the marginal propensity to consume out of rapidly changing net interest expenses. We leverage high-frequency data on household consumption expenditures combined with detailed balance sheet and demographic information to examine how households' net-interest exposure affects their consumption response to interest rate changes. First, we estimate the consumption response using a comprehensive set of fixed effects to control for monetary policy endogeneity and, alternatively, high-frequency monetary policy instruments. Both approaches consistently show that households with higher debt net of deposits experience significantly weaker consumption growth following an interest rate increase. Our findings suggest that for every dollar increase in net interest expenses, consumption declines by 20 to 40 cents within the first year. Additionally, analyzing an unexpected, policy-induced increase in mortgage rates affecting a subset of Norwegian households in 2014, we find that consumption fell by 30 cents per dollar of higher interest expenses in the first year. While this policy-induced rate change may have been perceived as more persistent, all methods point to a yearly MPC out of interest expenses ranging from 0.2 to 0.4, aligning with MPC estimates for other types of income shocks.

What are the implications of our results for the macroeconomic effects of monetary policy? As noted in the introduction, household debt has increased faster than income in many countries over the past decades. In a dataset of advanced and emerging economies assembled by the OECD, the median country — when ordering countries by the percentage increase in household debt-to-income over the period — doubled its household sector debt-to-disposable-income ratio between 1995 and 2022.[52] In Norway, household debt increased from 124% of disposable income in 1995 to

[51] Relatedly, using cross-state variation in UI benefits, Ganong and Noel (2019) find that an additional dollar in benefits at the onset of UI increases nondurable spending by 27 cents.

[52] OECD (2024), Household debt database, https://www.oecd.org/en/data/indicators/household-debt.html

253% in 2022. Using a back-of-the-envelope calculation, we would expect the percent change in consumption due to the cash-flow effect to equal MPC $\times$ (Δ lending rate) $\times$ ($\frac{\text{debt/income}}{\text{consumption/income}}$). Assuming an MPC of 30%, close to full pass-through of borrowing rates to lending rates, an average consumption to income ratio of 0.7, and an increase in the debt/income ratio of 129 percentage points, the aggregate consumption would have fallen by 55 basis points more in 2022 than in 1995 due to the increase in household indebtedness alone. That increase amounts to as much as half of the average consumption response to monetary policy in our sample period.[53]

Furthermore, our estimates can be used to shed light on the cross-country differences in the strength of the cash-flow channel of monetary policy. In the United States, fixed-rate mortgages account for more than 90% of home loans, most of which have an initial fixation period of 30 years. As a result, there is a very slow pass-through of rising policy rates to average mortgage rates. Based on our MPC estimates, if a country with the household debt/income ratio of the United States – of around 100% – would go from having only floating-rate debt to only long-term fixed rate debt, then, *ceteris paribus*, a one percentage point exogeneous increase in the policy rate would lower consumption by around 40 basis points less in the short run.

(accessed on December 6, 2024).

[53] Similar calculations were made by Bache (2024) based on an earlier version of our paper.

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Appendix

A Data structure and aggregation

This aggregation of the transaction data by location and consumer category is based on underlying metadata stored with each transaction by Nets. Table A1 presents all variables in the raw data provided by Nets to Norges Bank. In addition to the number and amounts of transactions per person per week, consumer category and location, each observation includes a set of individual demographic characteristics: birth year and gender. For debit card transactions, the data also includes a variable recording cash withdrawals made during the purchase (cashback). However, ATM cash withdrawals are not included in the data.

The consumption categorization is based on 24 COICOP groups and contains all 12 top level codes such as “Food and beverages”, “Restaurants and hotels” and “Clothing and footwear” and “Housing, water, electricity, gas”.[54] Some top-level categories are further divided into second-level COICOP groups. Additionally there are two categories (13 and 14) which apply only to bank wire transfer, bringing the the total to 26 categories. Table A2 lists all categories.

The aggregation by geography and consumer categories is based on seller type and location information. The consumer categorization is based on the United Nations’ 1999 COICOP classification.[55] As COICOP codes are not part of the metadata that the data provider stored with each individual transaction, we provided Nets with a cross-walk between the metadata and COICOPs to facilitate the aggregation.

For debit card transactions, the metadata contains the date of the transaction, the location (zip code) of the the card terminal, and the business name, NACE Rev. 2 and Merchant Category Code (MCC) of the store. Aggregation by location is based on the four-digit zip code the card terminal is registered at,[56] while aggregation by COICOP is based on the MCC code registered to the card terminal.[57]. Aggregation by COICOP codes is obtained through a cross-walk between MCC and COICOP. Out of 162,000 card terminals, 42,600 were classified with MCC "Miscellaneous and Speciality Retail Stores" (MCC=5999) or had missing MCC. These terminals were classified using the metadata registered on the terminal, typically the name or NACE Rev 2. code (five-digit Norwegian SN07) of the store.[58]

For bank wire transfers, the transaction metadata includes the transaction date and the creditor’s NACE Rev. 2 and location (zip code). Aggregation by location is based on the four-digit zip code, while aggregation by the consumption categories listed in Table A2 is based on a mapping between the NACE Rev 2. code (five-digit Norwegian SN07) and COICOP.[59] Two types of wire transfers, categorized as non-COICOP categories 13 and 14, include transfers between persons and banks (13) and between persons and government institutions (14).

[54] COICOP is an abbreviation for Classification of Individual Consumption According to Purpose, developed by the United Nations Statistics Division.

[55] The COICOP classification was revised in 2018. The top level structure (first and second level), the level at which our electronic payments are aggregated, remained mostly unchanged. The main update was the introduction of more granular categories (at the fourth level).

[56] There are about 5000 such codes in Norway. To ensure that the combination of zip-COICOP does not identify expenditures classified as being sensitive (e.g. precise information on type of firm related to health expenditures), location information has been removed (replaced with -1) for certain combinations of COICOP-zip code.

[57] MCC is a four-digit number listed in ISO 18245 for financial services and is used to classify a business according to its main activity.

[58] The MCC-COICOP cross-walk and the classification of undefined (5999) or missing MCC stores by COICOP is available upon request.

[59] The cross-walk is available upon request

Table A1: Variable List

Data source	Variable	Description
All	*nb_lnr*	Anonymized personal id
All	*nb_faar*	Birth year (derived by Norges Bank)
All	*nb_kjonn*	Gender (derived by Norges Bank)
All	*faar*	Birth year (provided by Nets Branch Norway)
Debit card	*week_nr*	Year and ISO Week number (1-53)
Debit card	*consumer_category*	Consumption category
Debit card	*brukersted_postnummer*	Four-digit zip code of card terminal
Debit card	*tot_num_txn*	Number of transactions
Debit card	*kontantuttak_belop*	Cash withdrawal
Debit card	*varekjop_belop*	Purchase amount
Debit card	*beloep_totalt*	Purchase amount + withdrawals
Outgoing wire transfers	*week_nr*	Year and ISO Week number (1-53)
Outgoing wire transfers	*consumer_category*	Consumption category
Outgoing wire transfers	*postnr*	Four-digit zip code of creditor
Outgoing wire transfers	*tot_num_txn*	Number of transactions
Outgoing wire transfers	*belop*	Transaction amount

Notes: This table lists all variables in the raw data.

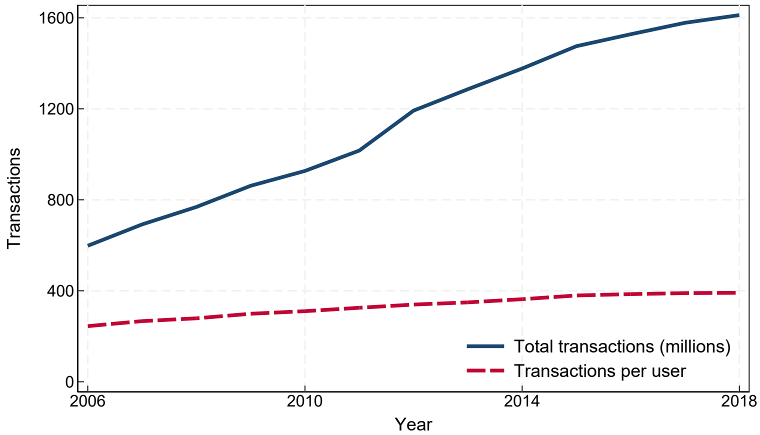
Table A2: Consumption categories

01	Food and non-alcoholic beverages	
02	Alcoholic beverages, tobacco and narcotics	
03	Clothing and footwear	
04	Housing, water, electricity, gas and other fuels	
05	Furnishings, household equipment and routine household maintenance	
06	Health	
07	Transport	
	071	Purchase of vehicles
	072	Operation of personal transport equipment
	073	Transport services
08	Communications	
09	Recreation and culture	
	091	Audio-visual, photographic and information processing equipment
	092	Major durables for outdoor recreation
	093	Other recreational items and equipment, gardens and pets
	094	Recreational and cultural services
	095	Newspapers, books and stationery
10	Education	
11	Restaurants and Hotels	
	111	Restaurants
	112	Hotels
12	Miscellaneous goods and services	
	121	Personal care
	123	Personal effects
	124	Social protection
	125	Insurance
	126	Financial services
	127	Other services
13	Payments to banks	
14	Payments to public institutions	

Notes: Aggregation level for consumption category. The category numbers corresponds to the 1999 COICOP version. Category 13 and 14 are not part of the COICOP classification, and apply only to bank wire transfers made via NICS.

B Data Figures and Tables

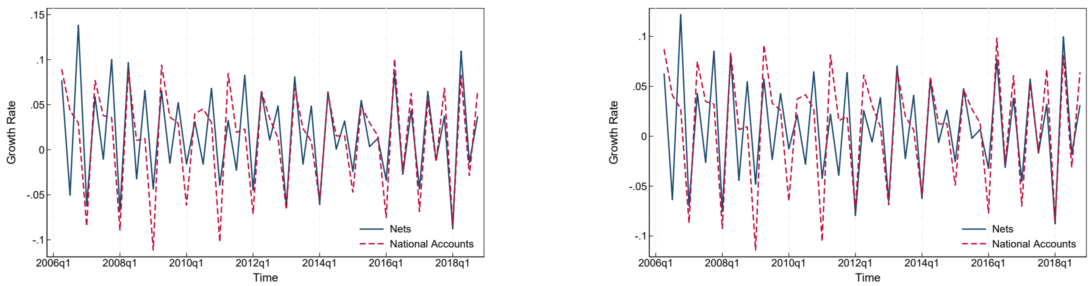
Figure B1: Debit Card Transactions: Total and per user



Notes. This figure plots the total transactions (in millons) and transactions per debit card user in our electronic transactions database.

Figure B2: Comparison with National Accounts (Growth).

(a) Total (b) Per Capita



Notes. This figure plots the quarterly growth rates of nominal household consumption (domestic + abroad) from the national accounts (dashed line) and aggregate household electronic expenditures (solid line). In panel (a) we use total amounts, while in panel (b) the national accounts is measured per-capita, and the electronic expenditures is measured per-user. For the electronic expenditure measure we remove single wire transfers above 100,000 NOK (12,500 USD2015), person-to-person transfers, and all transfers to banks, except imputed payments of credit card bills.

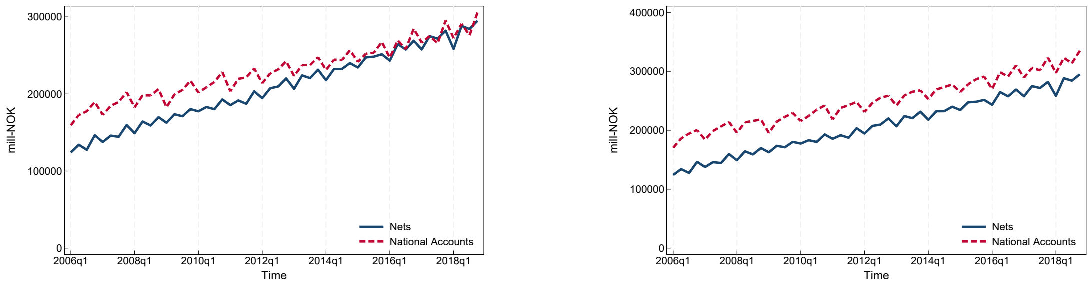
Table B3: Comparison with National Accounts

	A: Total	B: Per capita
(1) Domestic	(0.83,0.68)	(0.81,0.66)
(2) Domestic and Abroad	(0.77,0.59)	(0.75,0.56)

Notes. The table shows the correlation of various national accounts consumption measures with our electronic expenditures. In row (1), we use Norwegian households consumption inside Norway. In row (2) we use total consumption by Norwegian households. In column A we compare total value, while in column B we compare total value normalized by quarterly population (for national accounts) and by quarterly number of users (for electronic expenditures). The correlation refers to the Pearson correlation, while the R^2 is obtained from a linear regression.

Figure B3: Comparison with National Accounts (Level)

(a) Domestic (b) Domestic and Abroad



Notes. This figure plots the quarterly levels of nominal household consumption from the national accounts (dashed line) and aggregate household electronic expenditures (solid line). In panel (a) national accounts consumption is measured as Norwegian household consumption inside Norway, while in panel (b) national accounts consumption is measured as Norwegian household consumption in Norway and abroad.

C Credit card imputation

Payments to banks (category 13) include debt service payments, in particular mortgage payments. We impute and remove these payments by splitting category 13 invoice payments into two groups. The grouping is based on the whether a payment is likely to be consumption (e.g. credit card) or investment (e.g. mortgage) related, and we clean the data by removing transactions classified as the latter. The imputation is based on the assumption that service of investment related debt is relatively stable over time, in contrast to other payments to banks (e.g. credit card bills). The algorithm consists of 7 steps performed sequentially per individual. In each step, the payment is classified as imputed debt service if the condition is met and the transaction amount is above 2500 NOK (2018 CPI adjusted, equivalent to 310 USD at the 2015 exchange rate).

1. Local stable payment: Compute the moving coefficient of variation (standard deviation over mean) over a rolling window of 8 payments within a zip-code, dropping the largest and smallest payment.[60] For payments with multiple transactions within a week we first compute the average payment by dividing by the number of transactions. 7.2 percent of invoice observations in category 13 involve multiple transactions. The payment is classified as imputed debt service if the coefficient of variation is below 0.12.

2. Typical payment within a year: Re-classify the remaining 25 percent of transactions as

[60] For payments with multiple transactions within a week we first compute the average payment by dividing by the number of transactions.

imputed debt service if the first step classifies more than 75 percent of transactions within the year as imputed debt service.

3. First and last year adjustment (I): Classify all payments in the individual's first (last) year of observation as imputed debt service if all payments in the following (preceding) year are classified as imputed debt service. This adjustment is done because the moving coefficient of variation is missing for the first and last 4 observations.

4. First and last year adjustment (II): Assume that the first (last) 4 observations are imputed debt service payments if the 5th (T-4) observation is a mortgage payment.

5. Temporary non-mortgage: Re-classify as imputed debt service if more than 75 percent of observations in a window of +/- 2 observations are classified as mortgage payments.

6. Typical payment in full sample: Re-classify as imputed debt service if more than 70 percent of all observations are imputed debt service.

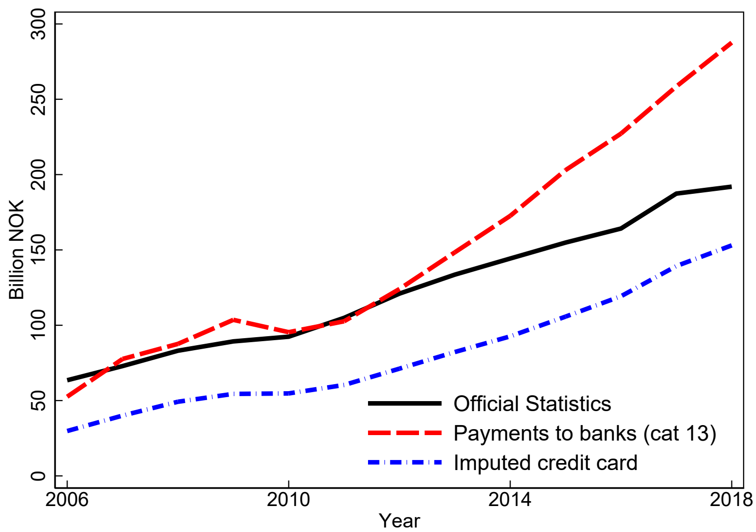
7. Very large payment: Re-classify as imputed debt service if the transaction amount is above $100,000$ NOK (2018 CPI adjusted, equivalent to $12,386$ in 2015 USD).

We know that certain payments in category 13 are related to debt service for one specific mortgage bank and one student debt bank, respectively. We separate these payments before applying the algorithm.[61] We nevertheless apply the algorithm on payments to these banks to check its performance. For the mortgage bank, our algorithm classifies 82.5 percent of the payments (correctly) as debt service. For the student debt bank, it classifies 91.2 percent of the payments correctly.[62]

[61] We can precisely identify these payments because in certain zip codes there is only one bank. For two of these unique banks, all payments by individuals are related to either mortgage or student debt.

[62] For the student debt bank, we do not apply the requirement that the transaction amount must be above 2500 NOK for it to be classified as imputed debt service.

Figure C4: Credit Card Coverage



Notes. This figure plots annual time series of official credit card payments (solid line) and total payments in consumption category 13 (dashed line). The dashed-dotted line represents our imputed credit card measure, obtained using the algorithm described in Section C. Source: Norges Bank (2023).

D Construction of monetary policy instruments

We construct four separate monetary policy instruments based on the first four forward rate agreements (FRA) based on the 3 month NIBOR rate. NIBOR is the reference money market rate in the Norwegian market. An FRA specifies a future interest rate and is used by market participants to hedge against interest rate risk. At a pre-determined expiration date, the seller of the contract pays the buyer the difference between the 3 month NIBOR rate at that date and the rate specified in the contract if that difference is positive, and vice versa. Hence, the FRA rate reflects the market's expectation of the 3 month money market rate at the expiration date plus a potential forward premium. The first FRA uses the upcoming International Money Market (IMM) date as its expiration date, the second FRA uses the next IMM date, and so on. Since there are four IMM dates in a year, the instruments reflect expectations of the money market rate from within the first quarter after a monetary policy announcement until around one year after the announcement. We construct our instruments for the time period from the monetary policy announcement in July 2004 until the last announcement in 2018.[63] The data is extracted from the 1 minute Thomson Reuters Tick History database maintained by Refinitiv.

Let FRA_d^i be the change in expectations associated with FRA contract i on announcement day number d ($d = 1$ is the first announcement day in our sample, $d = 2$ is the second one, and so on). Following Miranda-Agrippino and Ricco (2021), we run the regression

$$FRA_d^i = \alpha^i + \sum_{j=0}^{3} F_d^{NB} x_{q+j} \theta_j^i + \sum_{j=0}^{2} [F_d^{NB} x_{q+j} - F_{d-1}^{NB} x_{q+j}] \gamma_j^i + \overline{MPI}_d^i, \tag{D1}$$

[63]While the FRA data is available from 2001, the macroeconomic forecasts are only available starting in January 2004, and hence the first forecast revisions are available in the second quarter of 2004.

where $F_d^{cb} x_{q+j}$ is the forecast prepared by Norges Bank before announcement day d for the vector of variables x at horizon $q+j$. $F_d^{NB} x_{q+j} - F_{d-1}^{NB} x_{q+j}$ is the associated forecast revision. Here j denotes the number of quarters from the quarter q in which the forecast is prepared. Here $\overline{MPI}_d^i$ is the residual of the regression that uses FRA number i.

Over our sample period, Norges Bank has prepared and made public two types of forecasts. The first are the official forecasts published along with the triannual (until 2012) and quarterly (from 2013) Monetary Policy Reports. These forecasts are not suited to our needs, since they are only available for around half of the monetary policy meetings in our sample. Instead, we rely on a set of model-based forecasts produced by Norges Bank's system for averaging models (SAM). SAM forecasts are typically updated multiple times each quarter, and they are used as starting points to generate the official forecasts for the Monetary Policy Reports. They have typically also been published along with the official forecasts (see Aastveit et al. (2011) for a detailed description). We use the SAM forecasts for the quarterly GDP growth rate and the quarterly core inflation rate (CPI-ATE) in regression D1.

We now aggregate the residuals $\overline{MPI}_d^i$ from regression D1 to the monthly level by summing over meeting days within a month (there are very few months in which there are multiple meetings). We then project the monthly residuals $\overline{MPI}_t^i$ on twelve of their own lags by running the regression

$$\overline{MPI}_t^i = \phi_0^i + \sum_{j=1}^{12} \phi_j^i \overline{MPI}_{t-j}^i + MPI_t^i. \tag{D2}$$

As explained by Miranda-Agrippino and Ricco (2021), this step accounts for the possible slow absorption of information among market participants, which can make the instruments $\overline{MPI}_t^i$ autocorrelated. The four residuals $\{MPI_t^i\}_{i=1}^4$ constitute our final set of monetary policy instruments.

Figure E6 plots the four instruments both before and after adjustments for information and autocorrelation. The correlation between the unadjusted and the fully adjusted instruments is between 77 and 78 percent for all the four FRAs. The R^2 of the first-stage regression of the change in the money market rate on the four instruments is 10 percent.

Figure E7 shows the estimates from a local projection of the money market rate on an initial increase in the same rate, instrumented with our monetary policy instruments. We include one lag of the money market rate as well as month dummies and a second order polynominal in time.

E Additional empirical results

E.1 OLS with exposure groups

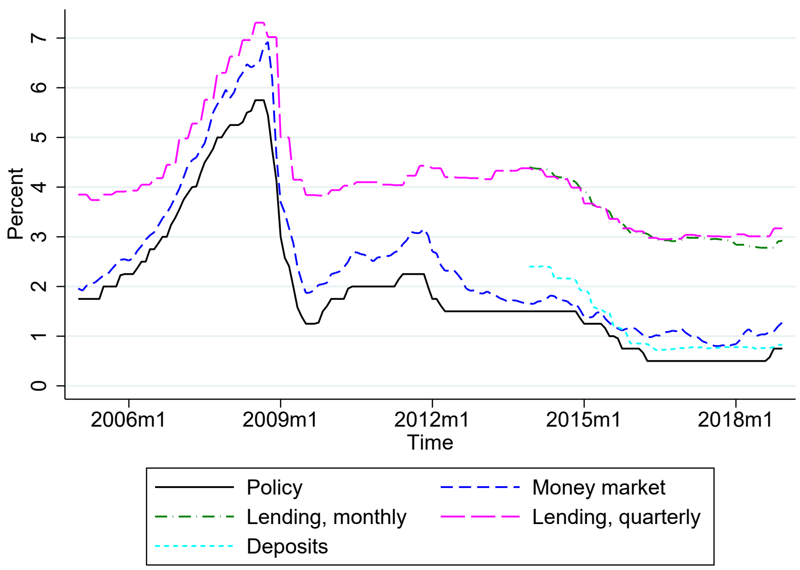
We re-specify regression 1 to allow for non-linearity across the distribution of interest exposure. This gives the regression

$$\frac{c_{i,t+h} - c_{i,t-1}}{y_{i,\text{year}_t - 1}} = \sum_{g=2}^{20} \beta_g^h \Delta r_t \times \mathbb{I}_{g,i,t-1} + \delta_i^h + \xi_t^h + \sum_{n=1}^{N} \gamma_{t,k}^{h,n} + X_{i,t}\alpha^h + \epsilon_{i,t}^h, \tag{E3}$$

where $\mathbb{I}_{g,i,t-1}$ is an indicator function that equals one if household i is in exposure group g based on income and liquid assets in year $t-1$. The excluded group is $l = 1$, the group of households with the lowest 5% exposure.

Figure E11 show the estimates of β_g^h for each group g and horizon h. All estimates are relative to the excluded group.

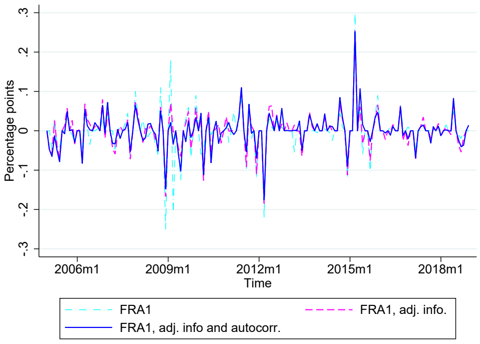
Figure E5: Interest rates.



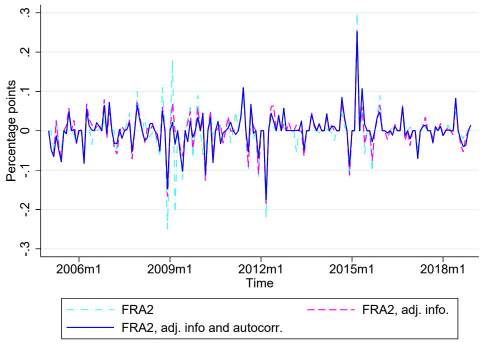
Notes. The figure shows interest rate series over our sample period 2006 – 2018. The policy rate is the interest rate on banks' overnight deposits in Norges Bank. The money market rate is the 3 month NIBOR rate. The monthly lending and deposit rates are the interest rates on all outstanding repayment loans and on deposits, respectively, for the household sector, both from a sample of banks and mortgage companies (these rates are only available starting in December 2013). The quarterly lending rate is from a full count of banks' and mortgage companies.

Figure E6: Monetary policy instruments.

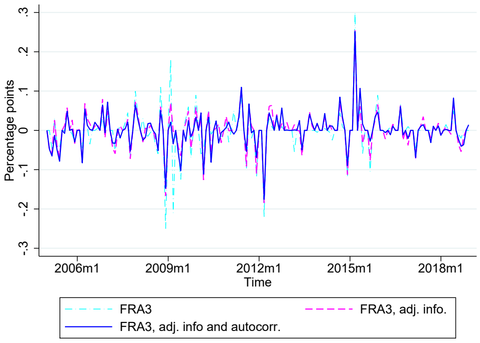
(a) FRA1



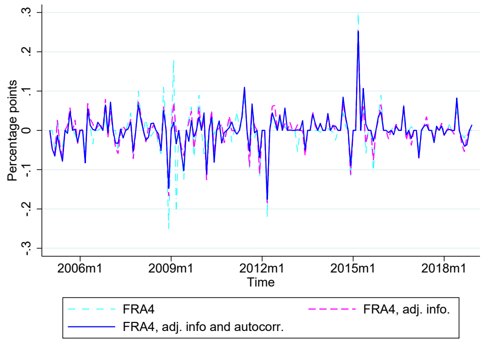
(b) FRA2



(c) FRA3

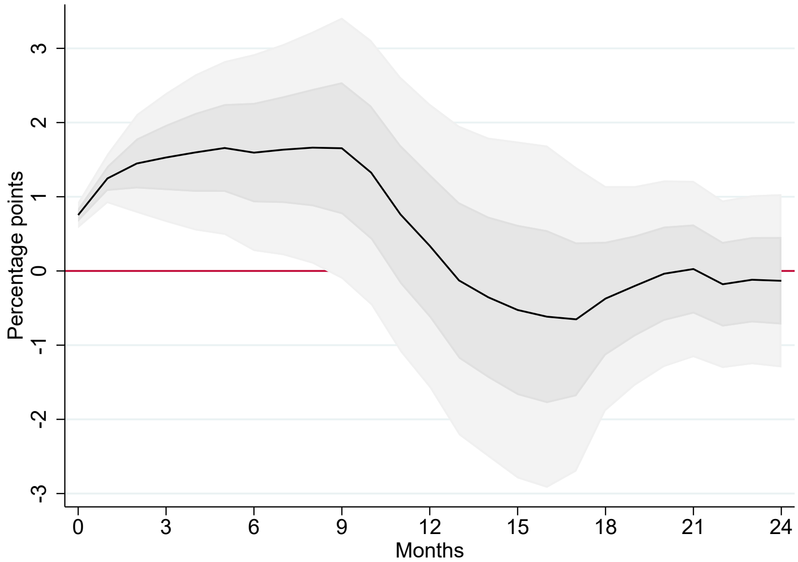


(d) FRA4



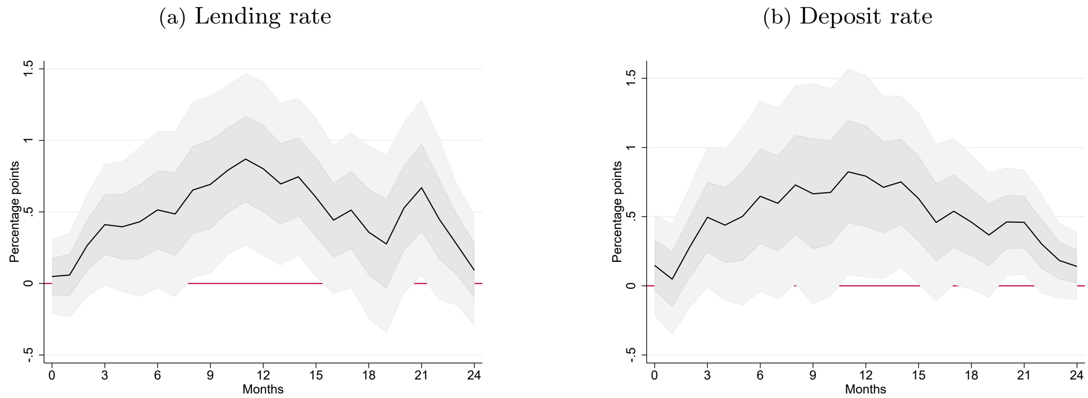
Notes. The figure shows the four monetary policy instruments used for the empirical specification in Section 3, before and after adjustments for, respectively, information effects and autocorrelation.

Figure E7: Interest rate after initial change.



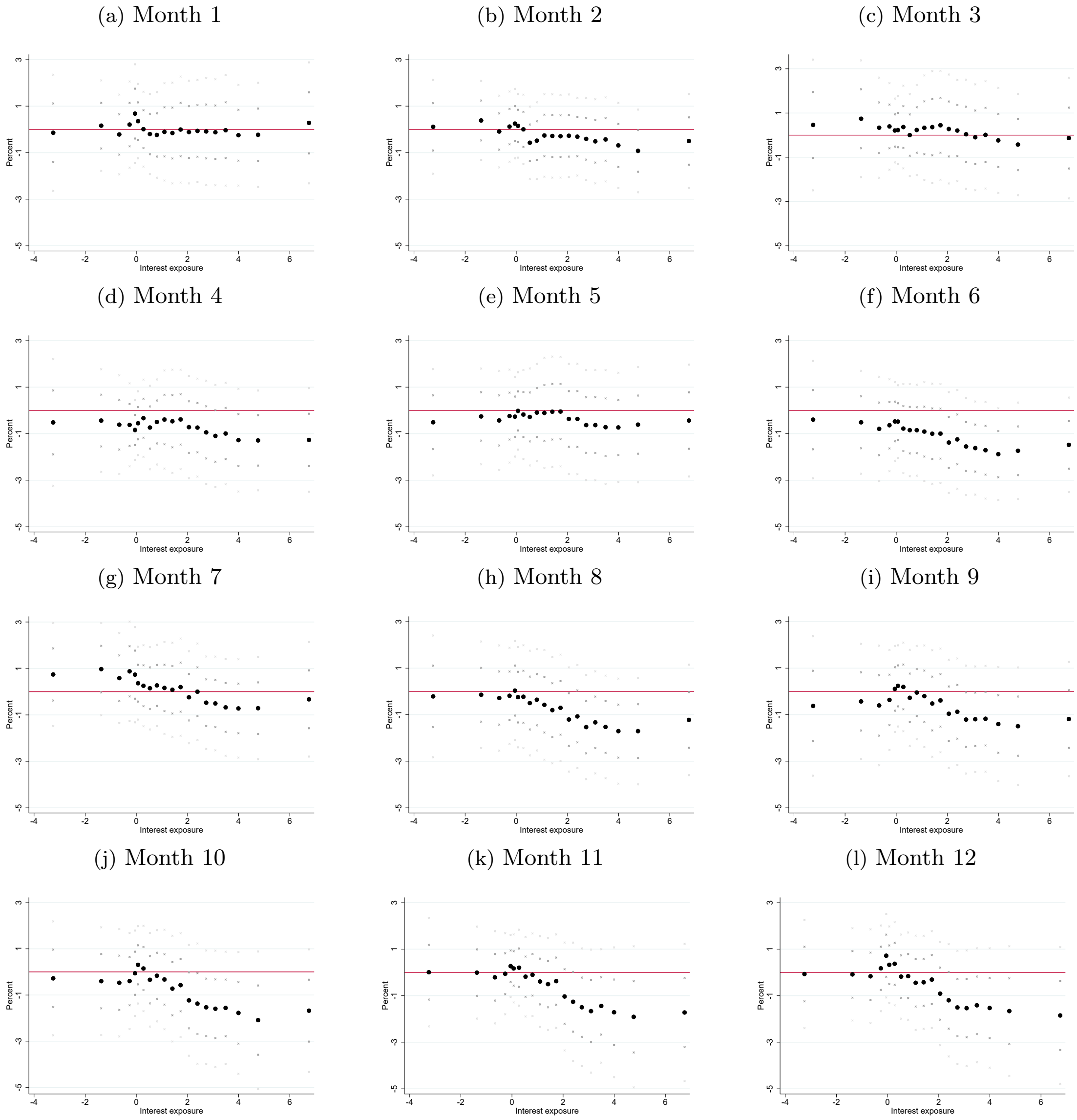
Notes. The figure shows the result of the local projection of the 3 month money market rate on the initial change $t = 0$ in the instrumented money market rate. The regression includes month dummies and a second order polynominal in time. See Section D.

Figure E8: Pass-through of money market rate to lending and deposit rates.



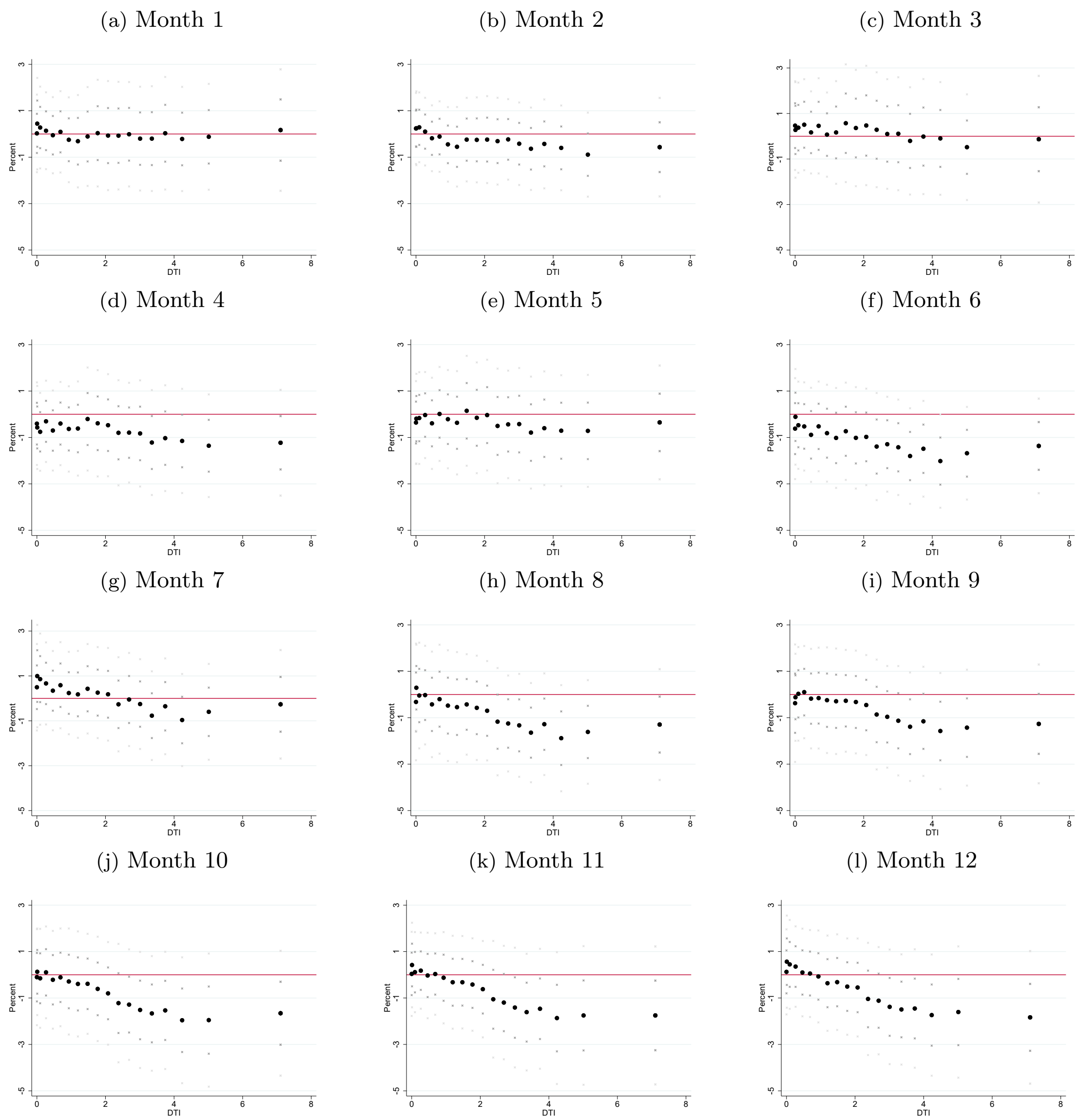
Notes. The figure shows the pass-through of an initial change in the 3 month money market rate to the lending and deposit rates, respectively, for the period December 2013 to December 2018. The regression is specified in Section 3.1.3.

Figure E9: Consumption response to 1 p.p. increase in interest rate, by interest exposure and month. IV regression 4.



Notes. The figure shows the results from regression 4 by time horizon and quantiles (20 ventiles) of households based on interest exposure (debt subtracted bank deposits and divided by income). Each subfigure shows a separate horizon of the local projection. Month 0 is the month of the instrumented interest rate change. The black dots show the coefficient β_g^h of the regression for a particular ventile g and horizon h. The median exposure for each of the ventiles is shown on the horizontal axis. The vertical axis shows the estimated response of consumption, relative to its level in the three months before the change in the interest rate, in percent of income.

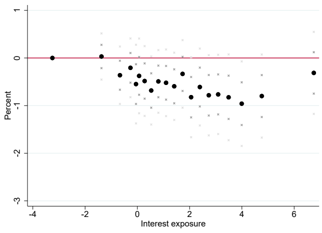
Figure E10: Consumption response to 1 p.p. increase in interest rate, by debt-to-income (DTI) and month. IV regression 4.



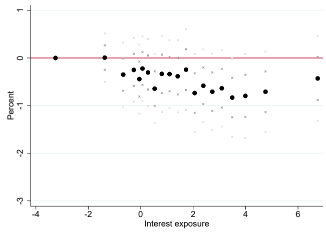
Notes. The figure shows the results from regression 4 by time horizon and quantiles (20 ventiles) of households based on debt-to-income (DTI). Each subfigure shows a separate horizon of the local projection. Month 0 is the month of the instrumented interest rate change. The black dots show the coefficient β_g^h of the regression for a particular ventile g and horizon h. The median exposure for each of the ventiles is shown on the horizontal axis. Because all the households in the bottom two ventiles have zero DTI, they are lumped together in the regression. The vertical axis shows the estimated response of consumption, relative to its level in the three months before the change in the interest rate, in percent of income.

Figure E11: Consumption response to 1 p.p. increase in interest rate, by interest exposure and month, relative to group 1. OLS regression E3.

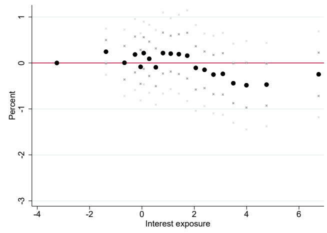
(a) Month 1



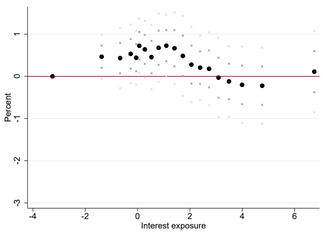
(b) Month 2



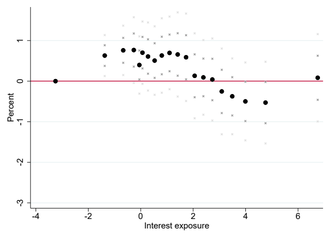
(c) Month 3



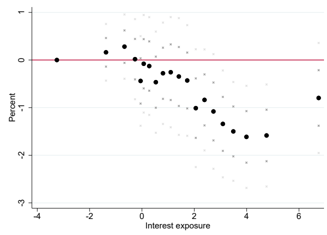
(d) Month 4



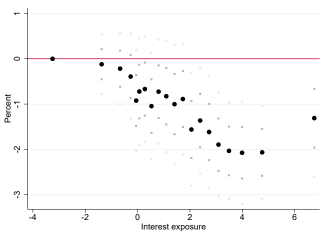
(e) Month 5



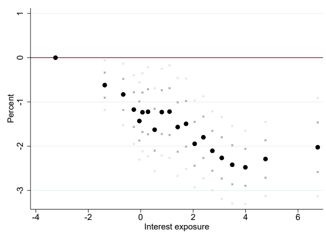
(f) Month 6



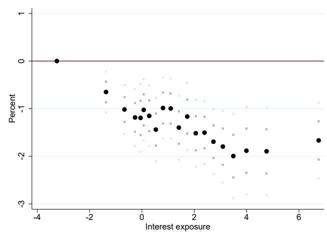
(g) Month 7



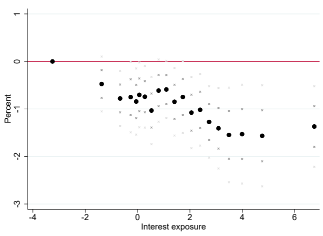
(h) Month 8



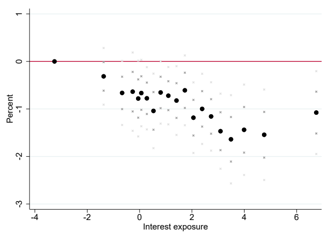
(i) Month 9



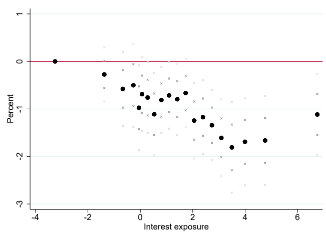
(j) Month 10



(k) Month 11



(l) Month 12



Notes. The figure shows the results from regression 1 by time horizon and quantiles (20 ventiles) of households based on interest exposure (debt subtracted bank deposits and divided by income). Estimated effects are relative to the reference group, the first ventile of interest exposure. Each subfigure shows a separate horizon of the local projection. Month 0 is the month of the interest rate change. The black dots show the coefficient β_g^h of the regression for a particular ventile g and horizon h. The median exposure for each of the ventiles is shown on the horizontal axis. The vertical axis shows the estimated response of consumption, relative to its level in the three months before the change in the interest rate, in percent of income.