The Zero Lower Bound on Household Deposit Rates: Not As Binding As We Thought*

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Abstract

I present novel evidence on the prevalence of negative household deposit rates, which challenges the notion of their perceived zero lower bound. Between May 2019 and April 2022, a total of 483 German banks introduced negative interest rates on household deposits. I study the effects of the adoption of these negative rates on banks' balance sheet positions and their role for the transmission of monetary policy by conducting a staggered difference-in-differences analysis. For this purpose, I compile a novel dataset, which is merged with official data from the Research Data and Service Centre of the German Bundesbank. Household deposits are reduced by up to 3% within twelve months after the introduction of negative household deposit rates. Additionally, credit creation is positively affected, which serves as evidence for an operative bank lending channel of monetary policy under negative household deposit rates. Thus far, this channel has been regarded as muted due to the perceived zero lower bound of household deposit rates.

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1 Introduction

The challenging economic situation in the aftermath of the Global Financial Crisis has prompted many central banks to implement accommodative monetary policy measures. When interest rates approached the zero lower bound (ZLB) without showing the hoped-for effects, central banks resorted to unconventional monetary policy measures, such as negative interest rate policy (NIRP), which is defined as one or more policy rates of a central bank being set to a level below zero.

Due to their unprecedented nature, the emergence of negative policy rates sparked a lot of controversy and uncertainty about their effects and potential repercussions on both the financial sector and the real economy. Notably, early contributions to the academic literature in this field highlighted the differential pass-through of negative policy rates to loan rates and other market rates on short-term debt opposed to deposit rates. Studies such as Jobst and Lin (2016) and Heider et al. (2019), shed light on this phenomenon, documenting that while the pass-through to loan and other short term market rates was still intact under negative interest rates, deposit rates were downward sticky around zero. However, a more recent contribution by Altavilla et al. (2022) has amended this finding by showing that the zero lower bound is not as binding anymore for corporate as it is for household deposit rates.

In this paper, I contribute to the literature on negative interest rate policy in three ways.

First, I compile a novel data set that challenges the downward stickiness of deposit rates around the ZLB. Over the period spanning from May 2019 to April 2022, a total of 483 German banks introduced negative interest rates on household deposits, which were complemented by exemption thresholds only above which the negative remuneration was effectively applied.[1] These banks, henceforth referred to as NIR-banks, account for more than 25% of all German banks. To the best of my knowledge, this paper is the first to document the prevalence of negative household deposit rates on a broader scale. It builds upon prior contributions such as those by Heider et al. (2021) and Eisenshmidt and Smets (2019), which identified a rigid zero lower bound on household deposit rates. Compared to these papers, this study extends the time horizon under investigation until the conclusion of NIRP in July 2022 and looks beyond the average of overnight household deposit rates across the Euro Area.

Second, I conduct an empirical analysis to study the effects of the introduction of negative household deposit rates on various balance sheet positions of these NIR-banks. Are household deposits of the afflicted banks affected in a significant way? If yes, how? And is credit creation impaired? To address these questions, the novel data set on German NIR-banks is merged with balance sheet data and data on profit and loss accounts, provided by the Research Data and Service Centre (RDSC) of the German Bundesbank.

[1] 10 of these banks are charging fees on private deposit accounts instead of interest rates, resulting in a factual negative remuneration.

To estimate the effects on banks' balance sheet positions, I use a difference-in-differences (DiD) analysis, for which treatment is defined as the staggered introduction of negative household deposit rates. The key identifying assumption of the empirical analysis is that, conditional on unit and time fixed effects as well as observable control variables, changes in the amount of household deposits of banks that have not introduced negative household deposit rates provide a suitable counterfactual for changes in the amount of household deposits that would have been observed in NIR-banks absent of treatment.

Considering recent advancements in the theoretical DiD literature that address challenges associated with two-way fixed effects (TWFE) regression under staggered rollout with potentially time-varying treatment effects (Athey & Imbens, 2022; De Chaisemartin & d'Haultfoeuille, 2020; Goodman-Bacon, 2021; Sun & Abraham, 2021), I employ estimation strategies robust to these concerns. The preferred specification entails the estimator proposed by Callaway and Sant'Anna (2021), which is supplemented by the approach outlined in Borusyak et al. (2023).

The main result is that banks which introduce negative household deposit rates, experience a statistically significant reduction in household deposits of up to three percentage points within twelve months. The reduction in household deposits occurs in spite of the sizable exemption thresholds for the negative remuneration. These thresholds often exceed the average wealth holdings of Germans in deposit accounts, as indicated by official statistics. This suggests that a zero interest rate might be a focal point, as posited by Heider et al. (2021), and rate cuts below this rate might be particularly salient. Alternatively, customers may have doubted the credibility of high exemption limits, anticipating banks to lower them, or they may have anticipated substantial inflows of funds in the near future.

Third, I provide evidence for an operative bank lending channel of monetary policy by showing that loans increase by up to two percentage points after the introduction of negative household deposit rates.[2] From the policymaker's perspective, the increase in household loans is encouraging since it indicates that, after policy rates transmit to household deposit rates, credit creation is positively affected. One potential reason for this finding is that, besides reducing the amount of household deposits, increasing credit creation is another way for banks to reduce their excess reserve holdings at the central bank. Reducing these excess reserves, which were remunerated at a negative rate during that time, mitigates the burden due to punitive interest payments. Another potential mechanism is that some banks become financially less constrained after having introduced negative deposit rates, allowing them to increase credit creation (see e.g. Jiménez et al., 2012; Kashyap & Stein, 2000, for the effects of monetary policy on financially constraint banks). Thus far, the literature has regarded this channel as muted given the perceived downward stickiness of household deposit rates.

[2] To be more precise, the bank lending channel posits that lower policy rates transmit to lower loan rates and thereby increase credit creation. The channel postulated in this paper works through a reduction in household deposit rates. The dynamics of loan rates are not discussed due to the unavailability of data on bank-level loan rates.

The results of this paper suggest that NIR-banks have been able to adequately replace household deposits by other sources of funding without experiencing detrimental effects on their performance. This is supported by anecdotal evidence obtained during the data collection process, according to which the reduction in household deposits was desired by the banks that have introduced negative household deposit rates. As already mentioned, by reducing household deposits, they were able to reduce the amount of reserves held at the central bank and, thereby, alleviate the pressure on their profitability.[3]

The evidence presented in this paper complements existing findings regarding the ramification of negative policy rates (see, for instance, Basten & Mariathasan, 2023; Demiralp et al., 2021) and negative corporate deposit rates (Altavilla et al., 2022) by studying the effects of negative household deposit rates on banks' balance sheet positions as well as for the transmission of monetary policy. In contrast to previous contributions by Heider et al. (2021) and Eisenshmidt and Smets (2019), I use self-collected data on the bank level instead of average overnight household deposit rates at the country level. This allows me to uncover dynamics that have not been considered up to this point, offering important implications for both current and future research on the topic of negative interest rates. For example, numerous empirical studies rely on mechanisms that use the asymmetric adjustment of loan and deposit rates to negative nominal interest rates to rationalize their findings. In Molyneux et al. (2019), the authors argue that sticky deposit rates are one of the reasons for compressed interest margins which in turn lead to eroding capital bases and eventually a fall in profits. Similar arguments can be found in Heider et al. (2019) and Lopez et al. (2020).

Likewise, several theoretical papers use the zero lower bound on household deposit rates as an established assumption in their models (see e.g. Abadi et al., 2023; Eggertsson et al., 2019; Ulate, 2021). While the results of this paper do not refute any of the aforementioned assumptions or mechanisms, they are put under scrutiny by showing that a sizable fraction of German banks opted to go below zero on their household deposit rates.

The remainder of the paper is structured as follows. In Section 2, I describe the self-collected data set as well as the data provided by the RDSC. Then, I present a descriptive analysis, discussing the most important facts related to the occurrence of negative household deposit rates. In Section 3, I briefly discuss the empirical strategy before turning to the main results in relation to the introduction of negative household deposit rates.[4] At the end of this section, I present some additional results. Section 4 addresses some issues concerning the robustness of the empirical analysis and Section 5 concludes.

[3]Moreover, the introduction of negative household deposit rates may deter potential new customers, further reducing the potential pressure on bank profitability.

[4]Parts of the methodology are based on very recent advancements in the difference-in-differences literature and, hence, deserve a more thorough explanation. This is provided in Appendix A.

2 Data and Descriptive Analysis

2.1 Data Sources and Terminology

The core element of the empirical analysis is a novel, self-collected dataset containing detailed information on banks that have introduced a negative interest rate on household deposits.

The basis for the data set on NIR-banks was collected from the price comparison websites Verivox and Biallo, which kept a record of banks that have introduced negative household deposit rates. This rudimentary dataset, which included only the names of NIR-banks, was amended with self-collected data that provided detailed information on these banks. This additional information consists of the rate of remuneration, the date of introduction and abolition of negative household deposit rates as well as details on the exemption thresholds, above which the negative remuneration applied. At the conclusion of the collection process, data on the date of the first introduction of negative household deposit rates was successfully collected for 341 of 483 banks that have introduced them.

In the final data set, the self-collected data is merged with data sets provided by the Research Data and Service Centre (RDSC) of the German Bundesbank. The data sets provided by the RDSC cover the universe of German banks and consist of the balance sheet statistics (BISTA), selected master data for monetary financial institutions (MaMFI) and the banks' profit and loss accounts (GuV). The final data set has monthly frequency and runs from May 2018 to June 2022. Variables are recorded in units of €1000. Additional information on the data collection process and the data sources are provided in Section 6.1 of Appendix A.

Concerning the terminology, the term 'deposits', which is used throughout this paper, refers to the banking products of a 'Girokonto' or 'Tagesgeldkonto'. These are the German equivalent to a current, checking or deposit account. To be more precise, a 'Girokonto' is defined as an account with the main purpose of accommodating any transaction within the payment system. Funds on this account are readily available without any period of notice, but it typically pays less interest than other banking products. The 'Tagesgeldkonto' has to be connected to a deposit account and funds can be instantaneously transferred from one account to the other. However, the 'Tagesgeldkonto' itself is not integrated in the payment system and, hence, cannot be used for payment transactions. As such, this account is intended as a simple and flexible savings account without any agreed upon maturity, paying a slightly higher interest rate than an ordinary deposit account in normal times. Negative interest rates for households were introduced primarily for the 'Girokonto', but whenever a 'Tagesgeldkonto' was available the same rate of remuneration applied.

2.2 Descriptive Analysis

The first result that challenges the notion of a binding zero lower bound on household deposit rates is depicted in Figure 1, which shows the geographical distribution of all NIR-banks, irrespective of whether the date of introduction has been successfully collected.[5] The location of a bank on this map of Germany is determined by the official location of its head office.

It can be seen that the majority of NIR-banks is located in states in the western part of Germany, with Bavaria and North Rhine-Westphalia exhibiting the highest number of NIR-banks. In states in the eastern part of Germany, on the other hand, relatively few banks have decided to introduce negative interest rates on household deposits. This still holds after dropping NIR-banks for which the date of introduction has not been successfully collected, which is depicted in Figure 14 in Appendix B.

However, in relative terms this finding reverses. While 43% of all German banks in states belonging to former Eastern Germany have introduced negative household deposit rates, this was only the case for 35% of all German banks in states of former West Germany. This is depicted in the right panel of Figure 2. This figure is based on a cleaned sample of the final dataset, which comprises 1190 banks, 422 of which have introduced negative household deposit rates at some point during the period of study.

The left panel of Figure 2 depicts the distribution of NIR-banks across the different types of banks. The majority of NIR-banks belongs to the second and third pillar of the German banking system, namely cooperative and public banks. These bank types are very prevalent in the German banking system and are characterized by their specific legal form. The category of 'Other Types' includes most notably big, regional and other commercial banks as well as state-owned banks. Out of the 236 banks in this category, only 23 have introduced negative deposit rates for households, while it was 399 out of 954 banks for the other two categories combined.

[5] Three banks that have introduced negative household deposit rates in 2016 and 2017 respectively have been dropped from the sample.

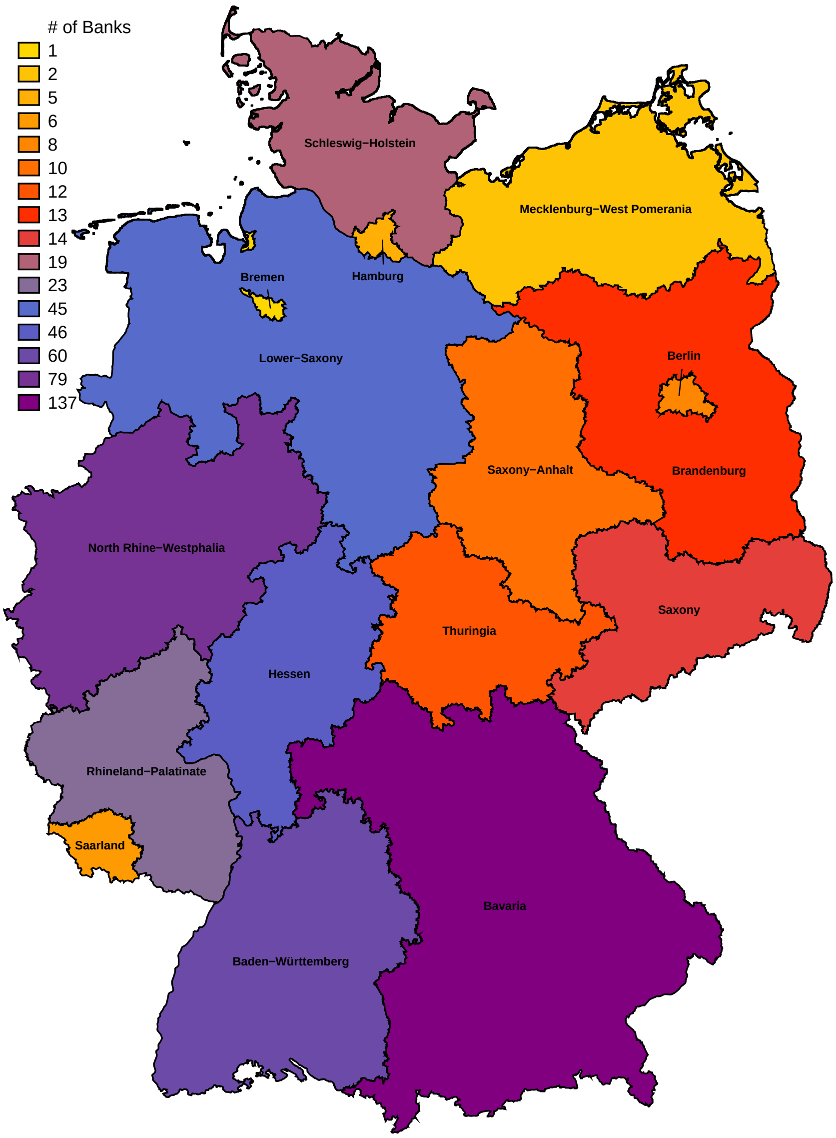

Figure 1: Geographical Distribution of NIR-Banks in Germany.
This figure shows the geographical distribution of all NIR-banks in Germany, irrespective of whether the date of introduction was successfully collected. The location is determined based on the official location of a banks' headquarter. Own illustration. Data source: self-collected dataset.

A potential mechanism explaining this finding is rooted in the structure of the German banking system. As shown by several studies and official banking statistics published by the OECD, the German banking system is on average less profitable than many of its international counterparts (Dombret et al., 2019). One main reason for this is the strong reliance on deposit financing of both cooperative and public banks which, once the associated downward stickiness of deposit rates is taken into consideration, makes it harder for these banks to pass on costs related to excess liquidity holdings. Furthermore, these banks follow the so-called house bank principle, according to which

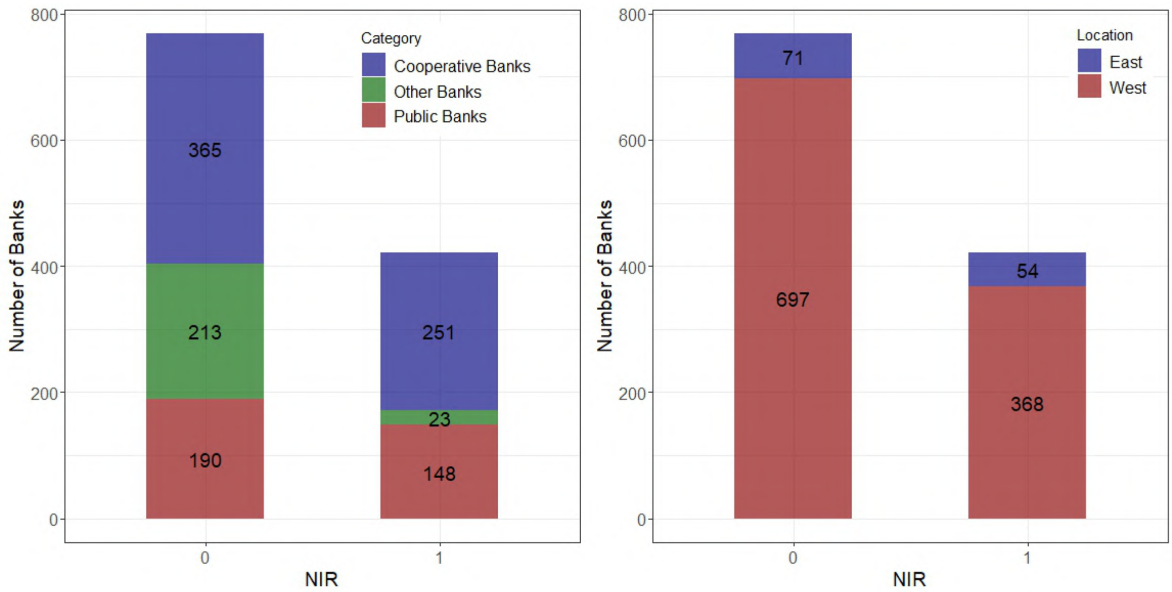

Figure 2: Distribution of NIR-Banks for Bank Type and East-West Location. This figure shows in the panel on the left the distribution of NIR-banks across bank types as recorded in the MaMFI dataset. The panel on the right shows the distribution of NIR-banks across states in East and West Germany as recorded in the MaMFI dataset. Own illustration. Data source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA 1999-2022, used in 2022, 2023 and 2024, own calculations.

profit maximization is not their primary objective (Harhoff & Körting, 1998). As a consequence, cooperative and public banks were disproportionately affected from persistent negative interest rate policy, which was exacerbated by an increase in excess liquidity in the banking system during the same time period. Eventually, this meant that it was primarily those banks that have introduced negative household deposit rates. A more detailed account of the German banking system is given in Section 6.2 of Appendix A.

Figure 3 shows the distribution of the dates of introduction of negative household deposit rates over time. In the panel on the left, the number of banks that have introduced negative household deposit rates in a given month is depicted, while the panel on the right depicts the cumulative number of banks having introduced negative rates up to a given date. Three points are worth noting here.

Firstly, no NIR-bank has abolished negative household deposit rates before the end of June 2022.[6] This was shortly before the ECB ended its negative interest rate policy by increasing the main refinancing rate to 0.5% and the deposit facility rate to 0%.

[6] Abolishing negative household deposit rates means that the bank set the negative remuneration equal to 0% rather than removing them from the contract. The latter would have required the notification and approval of the customers, while the former could be done at the banks' discretion.

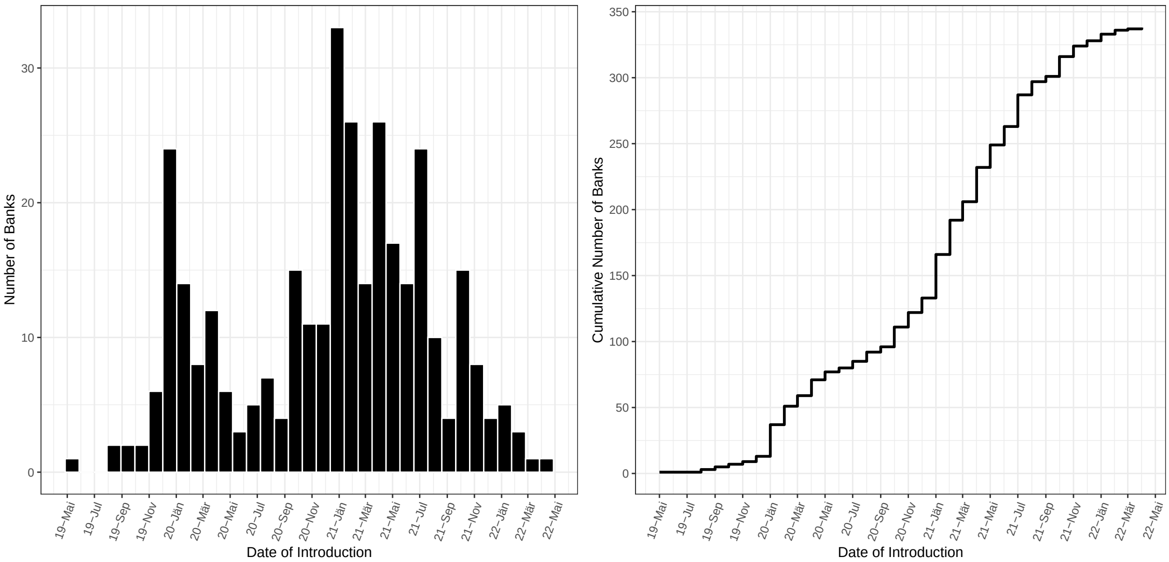

Figure 3: Date of the Introduction of Negative Household Deposit Rates.
This figure shows in the panel on the left the number of banks that have introduced negative household deposit rates in a given month. The panel on the right depicts the cumulative number of NIR-banks up to a given month. Own illustration. Data source: self-collected dataset.

Secondly, it can be seen that there is no clear pattern in introduction dates over time. This shows that a legislative change, which became binding in April 2021 after a ruling of the German Federal Court of Justice, had no visible impact on banks' decision to introduce negative household deposit rates. The legal change forced banks to have changes in their terms and conditions actively approved by their customers after April 2021, while it was previously sufficient to notify them.

Thirdly, the majority of German NIR-banks have only started to introduce negative deposit rates for households in early 2020. This is in line with several contributions in the literature, such as Lopez et al. (2020) and Heider et al. (2019), who assert that, while negative policy rates initially had rather benign effects, their full impact might only unfold at a later stage.

In the right panel of Figure 3, it can also be seen that the introduction of negative household deposit rates plateaued in early 2022, indicating that the adoption slowed down towards the end of the negative interest rate policy in the Euro Area. Anecdotal evidence suggests that banks anticipated the regime shift away from negative policy rates due to the global economic and political developments in early 2022, deterring them from introducing negative household deposit rates from then onward.

As mentioned before, most NIR-banks have introduced exemption thresholds in tandem with negative household deposit rates. Only funds held in excess of these thresholds have been subject to the negative remuneration. The left panel of Figure 4 depicts data on these exemption limits, which has been successfully collected for 286 NIR-banks. If the exemption threshold for a bank has changed over time, the average is depicted.

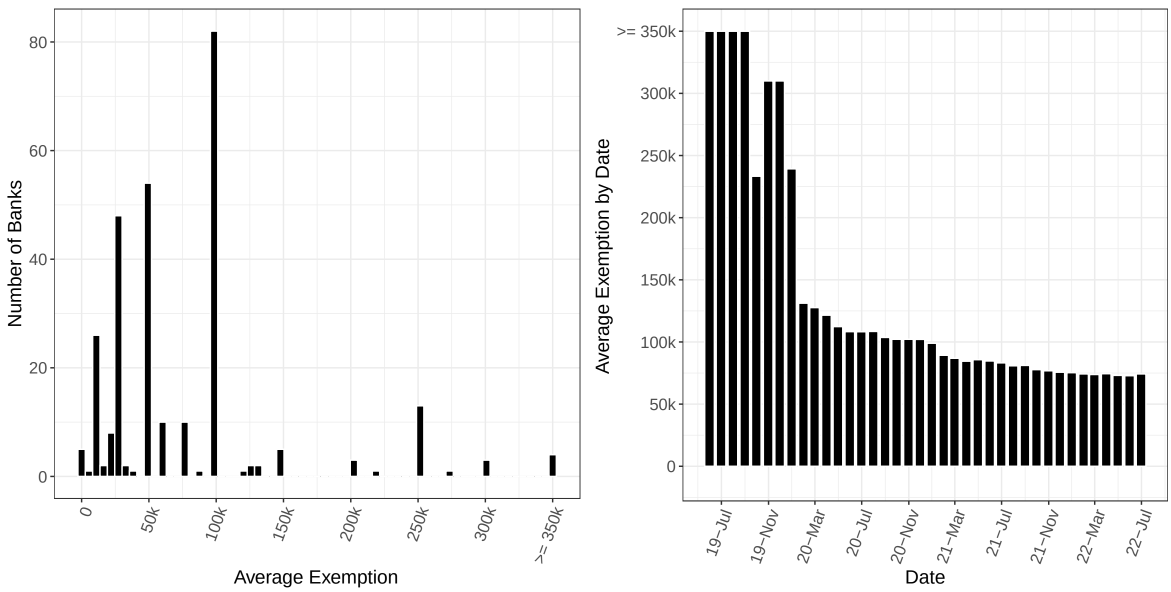

Figure 4: Histogram of Average Exemption Levels, Own Illustration.
This information is available 286 banks. If exemption levels have changed over time, the average of these exemption levels is depicted here. ; Data Source: Self-collected Data Set, own calculations.

Exemption thresholds are very disbursed and range from €0 to €500k, with the majority of NIR-banks setting limits up to and including €100k. 87 banks have introduced exemptions of up to €25k, another 81 banks are in the bracket of up to €100k and 82 banks have introduced exemptions levels of exactly €100k.

These numbers can be interpreted more sensibly when contrasting them with results from a Bundesbank (2023) report, which includes findings from a survey on both financial and non-financial wealth holdings of German citizens conducted in 2021. According to this report, Germans hold on average €12.7k in their deposit account, with the average in East Germany (€9.5k) being significantly lower than in West Germany (€13.6k). On that basis, only 32 banks, for which the exemption thresholds are known, have introduced limits low enough to effectively affect the average German's financial wealth holdings in these accounts. In other words, the majority of NIR-banks has not affected its average customer by introducing negative interest rates on household deposits.

The right panel of Figure 4 depicts the average exemption threshold over all NIR-banks that have introduced negative household deposit rates up to a certain point in time. The average exemption threshold decreased from approximately €125k in early 2020 to around €75k in 2022, indicating that banks became increasingly inclined to pass on the costs associated with negative interest rates to their private household customers by implementing more stringent policies.

Various summary statistics for relevant balance sheet variables are depicted in Table 1 in Appendix B. The variables are shown for the groups of NIR-banks, non-NIR banks and both of them together at two points in time, once at the beginning and once at the end of the sample. This serves as a crude approximation for the comparison of treatment and control group before and after the treatment occurs, as is usually done in non-staggered designs.[7] NIR-banks for which the date of introduction or key variables (e.g. deposits, loans, savings) are missing are omitted.

The distribution across banks for all variables is right-skewed, meaning that the average is significantly higher than the median. For example, the mean bank size in the sample is equal to approximately €5.4 billion, which is nearly five times as high as the median and twice as high as the 75th percentile. While this case is extreme, the pattern holds across all variables. On average, banks that have introduced negative household deposit rates are more deposit intense, bigger and hand out more loans. This is driven by the fact that most big German banks have decided to introduce negative household deposit rates.

Before turning to the results, I show that the sample of NIR-banks, for which the date of the introduction has been successfully collected, is representative for all NIR-banks. For this purpose, I present quantile-quantile plots, which compare the distributions of two groups for two bank characteristics, bank size and deposit intensity, at two points in time, once at the start and once at the end of the sample. Each point represents the cutoff value of a given decile of the respective distribution, where observations close to the 45 degree line indicate that the distributions are very similar. Figure 15 in Appendix B confirms that this is the case when comparing all NIR-banks, depicted on the y-axis, to the subsample of NIR-banks for which data on the adoption of negative household deposit rates is available, depicted on the x-axis. This serves as evidence that results based on this sample are representative for all German NIR-banks.

[7] Due to the dynamic assignment of the treatment, the depicted statistics should not be directly interpreted as evidence for or against the parallel trends assumption. Rather, they should be used to get some idea of the dataset.

3 Methodology and Results

3.1 Methodology

The main objective of this paper is to examine whether the adoption of negative household deposit rates had an effect on various balance sheet positions of banks, most notably household deposits and loans. For this purpose, it is necessary to use a methodology that estimates a causal relationship between the introduction of negative deposit rates and the dependent variable. In the empirical analysis treatment is defined as the staggered introduction of negative household deposit rates by banks and modeled as a binary variable. Moreover, the introduction of negative household deposit rates is endogenous because, contrary to a change in policy rates, banks decide themselves whether to introduce these negative rates. In such a setting, the most commonly used method is difference-in-differences, which allows for a time-invariant bias from selecting into treatment (Roth et al., 2023).

Assuming that the timing of treatment on the bank level is exogenous to the outcome variable conditional on bank-specific and time-specific fixed effects, treatment effects can be estimated in a DiD model with ordinary least squares (OLS). Its estimator is commonly referred to as the two-way fixed effects (TWFE) estimator. This approach has been used in various scenarios, including settings with a single or multiple treatment periods as well as homogeneous or heterogeneous treatment effects. However, recent contributions have shown that estimators obtained by a TWFE regression specification are potentially biased in many of these cases (De Chaisemartin & d'Haultfoeuille, 2020; Goodman-Bacon, 2021; Sun & Abraham, 2021).

The underlying reason for the arising biases is a problem of so-called 'bad comparisons' being included in the computation of the treatment effect, in which already treated units act as comparison units to later treated units. In this case, the difference between the effective comparison and later treated unit does not reflect the true treatment effect because the outcome change of the comparison unit over time might itself reflect a treatment effect.

I address the concerns associated with the TWFE estimator by applying diagnostic statistics proposed by Goodman-Bacon (2021) and De Chaisemartin and d'Haultfoeuille (2020) to show that the problems related to the TWFE estimator are not of first-order importance for this empirical analysis. Moreover, I employ additional estimation strategies that are robust to the aforementioned issue of bad comparisons. To be more precise, the estimators by Callaway and Sant'Anna (2021), short *CS*, and Borusyak et al. (2023), short *BJS*, are chosen.

On top of allowing for dynamic and heterogeneous treatment effects, they allow for the incorporation of time-varying control variables to relax the unconditional parallel-trends assumption to a conditional one. This leads to the following key identifying assumption for this empirical study: conditional on unit and time fixed effects as well as observable control variables, changes in the amount of household deposits of banks that have not introduced negative household deposit rates provide a good counterfactual for changes in the amount of deposits that would have been observed in NIR-banks absent of treatment.[8]

For a more thorough exposition of the empirical strategy I refer the reader to Appendix A, in which I discuss the results from the diagnostic statistics and the employed estimation strategies as well as some general assumptions that need to be satisfied in more detail. In particular, I elaborate on the differences between the approaches by Callaway and Sant'Anna (2021) and Borusyak et al. (2023) and how these affect the suitability of the respective estimator for the current study. Most importantly, the aforementioned estimation strategies differ with respect to the incorporation of time-varying control variables and the definition of the parallel trends assumption.

In the following sections, all models are estimated using the natural logarithm of the outcome variable, which is originally expressed in units of €1000. Clustering is done at the bank level, the unit at which treatment is assigned.[9] Confidence intervals are at the 95% level.

3.2 Main Results

The main result of this paper is presented in Figure 5, which depicts the effect of the introduction of negative household deposit rates on household deposits. Household deposits of German NIR-banks decrease by up to three percentage points within twelve months after the introduction of negative household deposit rates. Figure 5 shows the estimated coefficients for all three estimation techniques discussed in the methodological section. The treatment effects are statistically significant for all three estimators across the entire time horizon under study. The coefficients for the pre-trends, on the other hand, are not statistically different from zero. This indicates that the parallel trend assumption holds across all three estimation techniques.[10]

[8]After replacing household deposits by household loans, the same assumption holds for household loans as the dependent variable.

[9]According to Bertrand et al. (2004), the persistence in the treatment variable induces serial correlation in the error terms of the treated units, which should be adjusted for.

[10]Note that the pre-treatment estimates for the CS estimator are "short differences", i.e. comparisons between consecutive periods. On the other hand, pre-treatment estimates for the BJS and TWFE estimator are "long differences", i.e. comparisons between period t and the earliest available period. For a more in-depth explanation see Roth (2024).

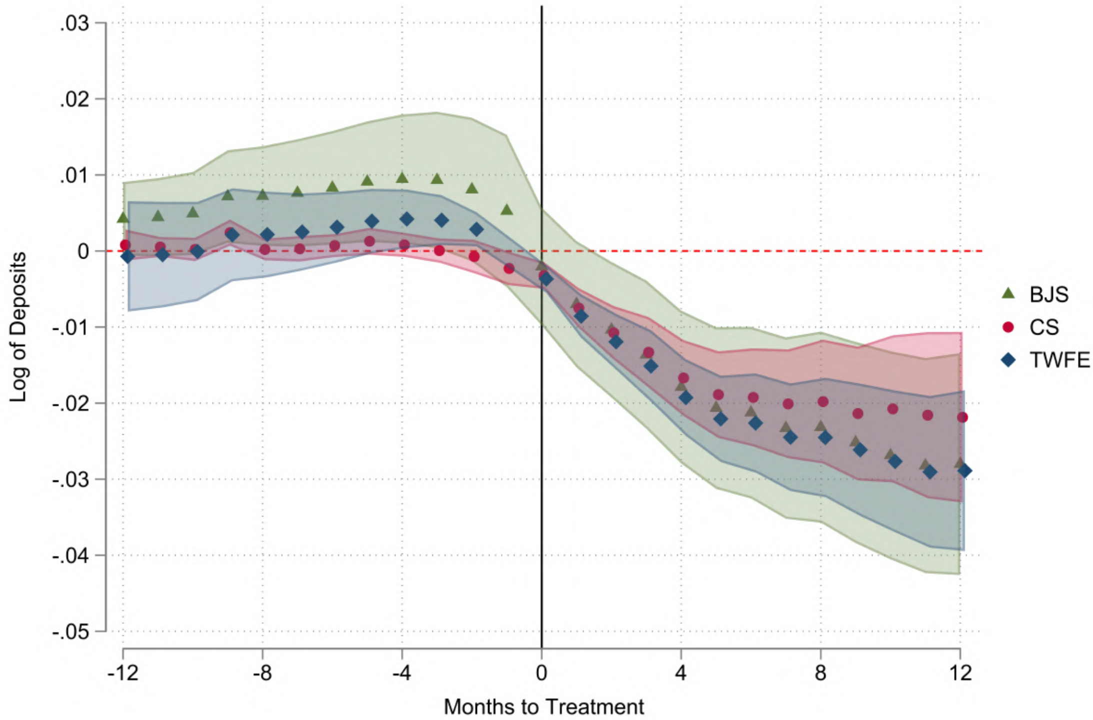

Figure 5: Event Study Plot of the Effect on Household Deposits.
This figure shows an event study plot of the introduction of negative household deposit rates on the amount of household deposits. BJS = estimator by Borusyak et al. (2023), CS = estimator by Callaway and Sant'Anna (2021), TWFE = two-way fixed effects. Own illustration. Data source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA 1999-2022, used in 2022, 2023 and 2024, own calculations.

Furthermore, the estimated effects are very similar across the three strategies, a first indication of the robustness of the results. This supports the evidence from the diagnostic statistics by De Chaisemartin and d'Haultfoeuille (2022) and Goodman-Bacon (2021) that the problems associated with the TWFE regression approach under staggered treatment adoption are not of major importance for the current study.[11]

Concerning the reasons for the decrease in household deposits, it is important to keep in mind that many NIR-banks concurrently introduced exemption thresholds when they adopted negative household deposit rates. As previously mentioned, only 32 NIR-banks have set low enough exemption limits such that the negative remuneration materially affected the average wealth holdings of Germans in such deposit accounts (Bundesbank, 2023). The significant reduction in household deposits in spite of these sizable exemption thresholds supports an argument made by Heider et al. (2021), according to which rate cuts in negative territory are more salient than rate cuts in positive territory.

[11] A recent paper by Chiu et al. (2023) finds that, while the TWFE estimator is often problematic from a theoretical point of view, the results from this approach are in many cases very similar to the ones obtained from more robust methods.

Additionally, exemption limits might not have been believed to be credible by customers and they expected them to decrease in the near future. Moreover, households' lower liquidity holdings and less-frequent needs to make large transactions should make it easier for them to substitute deposits for cash (see e.g., Brandao-Marques et al., 2021; Eisenshmidt & Smets, 2019). To the best of my knowledge, there is no evidence on such pronounced effects of deposit rate cuts in positive territory, suggesting that interest rate cuts in negative territory give rise to some behavioral responses that are not present in a positive interest rate environment.

The second main result is related to the balance sheet item that plays a pivotal role for the transmission of monetary policy to the real economy - loans. Figure 6 depicts the reaction of household loans to the introduction of negative household deposit rates for the same three estimation techniques as before. Depending on the estimation strategy, household loans increase between one and two percentage points within twelve months after the adoption of negative household deposit rates.

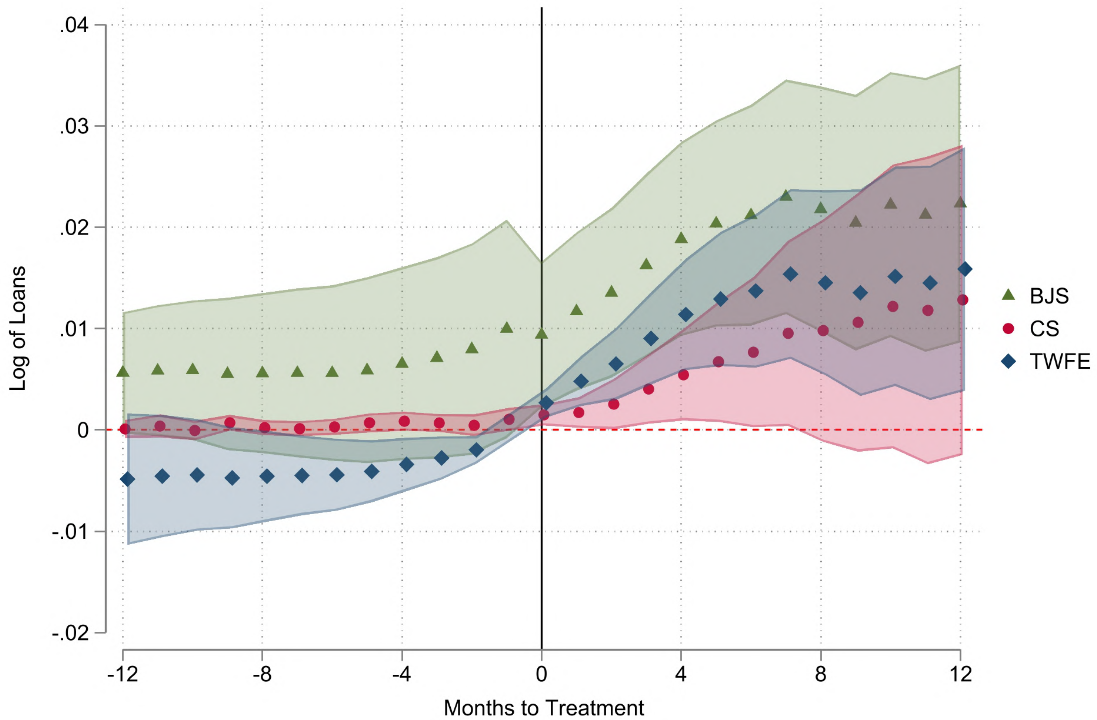

Figure 6: Event Study Plot of the Effect on Household Loans.
This figure shows an event study plot of the introduction of negative household deposit rates on the amount of household loans. BJS = estimator by Borusyak et al. (2023), CS = estimator by Callaway and Sant'Anna (2021), TWFE = two-way fixed effects. Own illustration. Data source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA 1999-2022, used in 2022, 2023 and 2024, own calculations.

Compared to the findings on household deposits, the results of the various estimation strategies with respect to household loans are a bit more mixed. The most likely reason for this is that the identification is not as clean as in the former case. Importantly, the effect on household loans might not be solely attributable to the introduction of negative household deposit rates, since concurrent changes on the supply side cannot be excluded or controlled for. Nevertheless, the statistical significance of the treatment effects across all three estimation strategies indicates that there is indeed a concurrent positive effect on credit creation.

From the policymaker's perspective, the increase in household loans following the introduction of negative deposit rates is an encouraging finding. It shows that, after policy rates transmit to household deposit rates, credit creation is positively affected. This is evidence for an operative bank lending channel of monetary policy after banks decrease their household deposit rates below zero. One potential reason for this finding is that, besides reducing the amount of household deposits, increasing credit creation is another way for banks to reduce their excess reserve holdings at the central bank. Reducing these excess reserves, which were remunerated at a negative rate during that time, mitigates the burden due to punitive interest payments. Another potential mechanism is that some banks become financially less constrained after having introduced negative deposit rates, allowing them to increase credit creation (see e.g. Jiménez et al., 2012; Kashyap & Stein, 2000, for the effects of monetary policy on financially constraint banks). Up to now, the literature has considered this channel as muted given the downward stickiness of household deposit rates.

Furthermore, the increase in credit creation suggests that NIR-banks have been able to adequately replace the loss in deposits by other sources of funding. Alternatively, it could be the case that NIR-banks have not experienced detrimental effects on their performance because the reduction in deposits itself eased the pressure on their profitability. The latter argument is supported by anecdotal evidence obtained during the data collection process, according to which the reduction in household deposits was desired by banks that have introduced negative household deposit rates. As already mentioned, by reducing household deposits, they were able to reduce the amount of reserves held at the central bank and, thereby, alleviate the pressure on bank profitability.

3.3 Additional Results

Household subsets. Figure 7 dissects the reduction of negative household deposit rates by breaking down domestic households in three subcategories, namely economically independent, employed and other households. The term households might be a bit misleading here because it refers to the owner of a deposit account rather than an actual household. While these two can potentially coincide, they do not necessarily have to. The first group comprises all self-employed individuals, the second group consists of all salary and wage earners, pensioners and unemployed people while the group of other households includes housewives, infants, schoolchildren, students and individuals not disclosing their occupation.

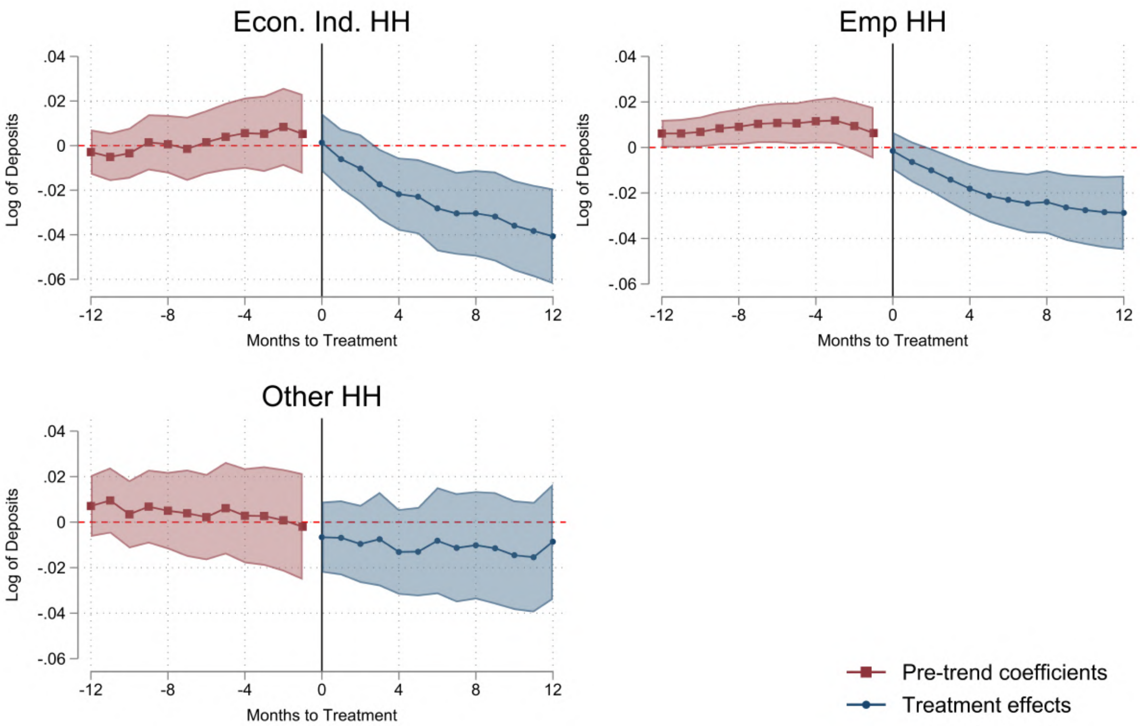

Figure 7: Event Study Plot of the Effect on Deposits of Subcategories of Domestic Households. Results for this graph are obtained with the BJS estimator. Own illustration. Data source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA 1999-2022, used in 2022, 2023 and 2024, own calculations.

Figure 7 shows that the reaction in household deposits differs significantly across the subcategories. Self-employed individuals display the strongest negative treatment effect with point estimates being as low as -4%. Employed households still show a statistically significant reduction in household deposits, while for the group of other households no significant treatment effect is reported. While the group composition is not ideal, given that unemployed and retired people are part of the category of employed households, the results indicate that higher income earners are more responsive to the introduction of negative household deposit rates.[12]

Only new vs. all customers. One facet of the adoption of negative household deposit rates that I have been silent about so far is that not all banks have introduced these negative rates for all customers alike. While most banks have introduced them for all of their customers, some banks opted to introduce the punitive interest payments only for new customers. For these banks, the aim of the policy was clearly to deter new customers from depositing with them rather than incentivizing existing ones to move their deposits. Figure 8 shows that, while all NIR-banks experienced a significant reduction in their household deposits after adopting negative rates, the effect was more sizable for banks that introduced them for all of their customers. This is not surprising since it concurrently deters new customers and incentivizes existing ones to shift their funds.

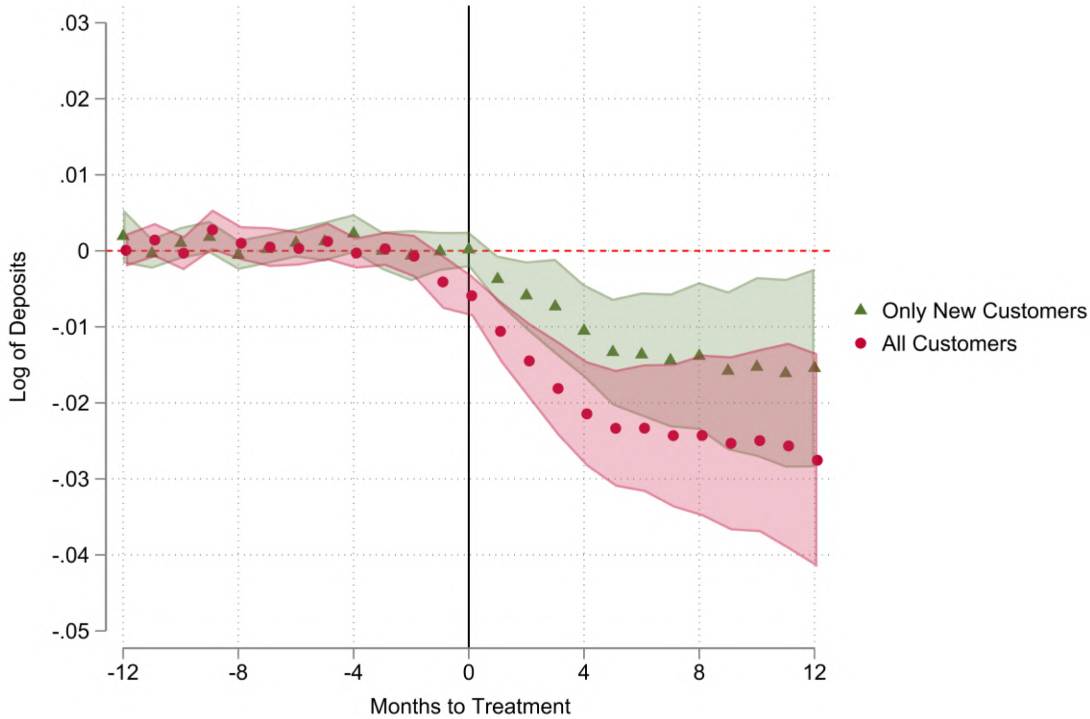

Figure 8: Event Study Plot of the Effects on Household Deposits for all vs. only new Customers
Results for this graph are obtained with the CS estimator. Own illustration. Data source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA 1999-2022, used in 2022, 2023 and 2024, own calculations.

[12]According to Fritsch et al. (2015), self-employed people earn on average more, however, the earnings distribution is also more unequal.

Bank type. The bank type also plays an important role for the response of household deposits after the introduction of negative deposit rates. Figure 9 separately depicts the treatment effects for public banks, credit cooperatives and the group of other banks. While the reaction of household deposits for credit cooperatives and public banks is negative, the group of other banks does not experience a reduction in their household deposits. The reason for the stronger effect on public banks and credit cooperatives, besides the relatively small sample for the group of other banks, is most likely rooted in the structure of the German banking system. Public banks and credit cooperatives are usually smaller banks that operate locally and have strong customer relationships. Furthermore, they follow the aforementioned house-bank principle, rather than having profit maximization as their first maxim. Consequently, these banks are disproportionately affected from persistent negative interest rate policy, making them more likely to introduce negative household deposit rates with potentially stricter terms.

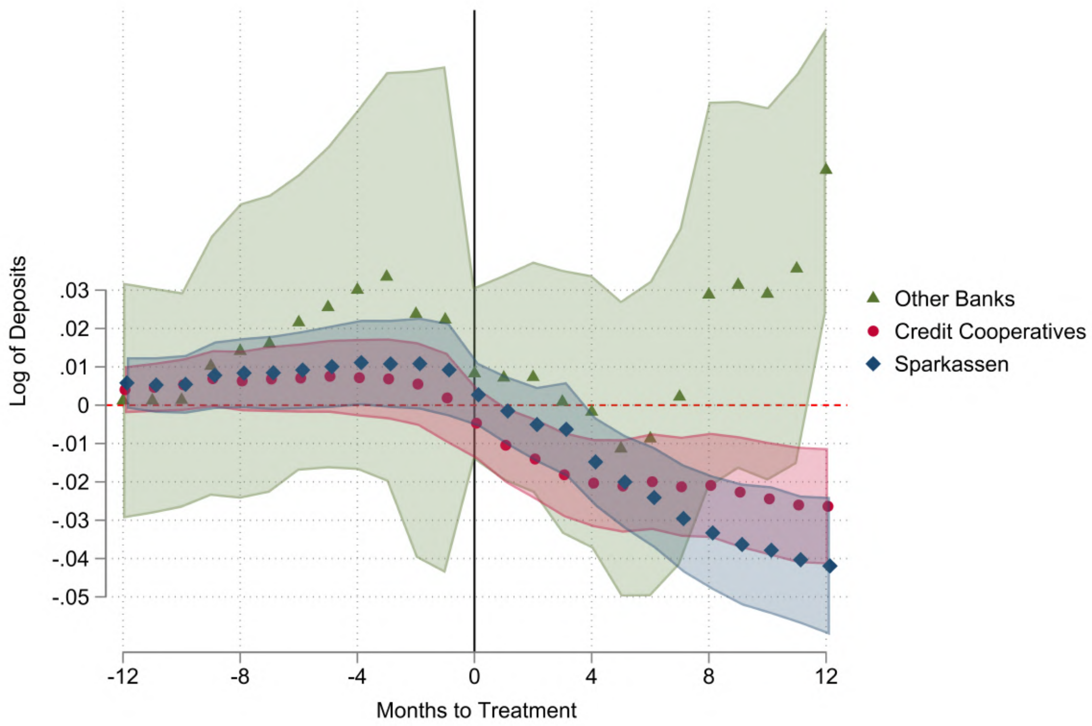

Figure 9: Event Study Plot of the Effects on Household Deposits by Bank Type.
Results for this graph are obtained with the BJS estimator. Own illustration. Data source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA 1999-2022, used in 2022, 2023 and 2024, own calculations.

Exemption thresholds. A further extension is to examine the role of the exemption thresholds in determining whether a bank experiences a reduction in household deposits after negative rates have been introduced. Figure 10 shows that exemption limits play a role, even though the results are not as stark as one might expect. Surprisingly, the treatment effects are very similar for all groups with exemption limits of up to €100k. In line with intuition, banks with exemption limits in excess of €100k do not experience a statistically significant reduction in household deposits.

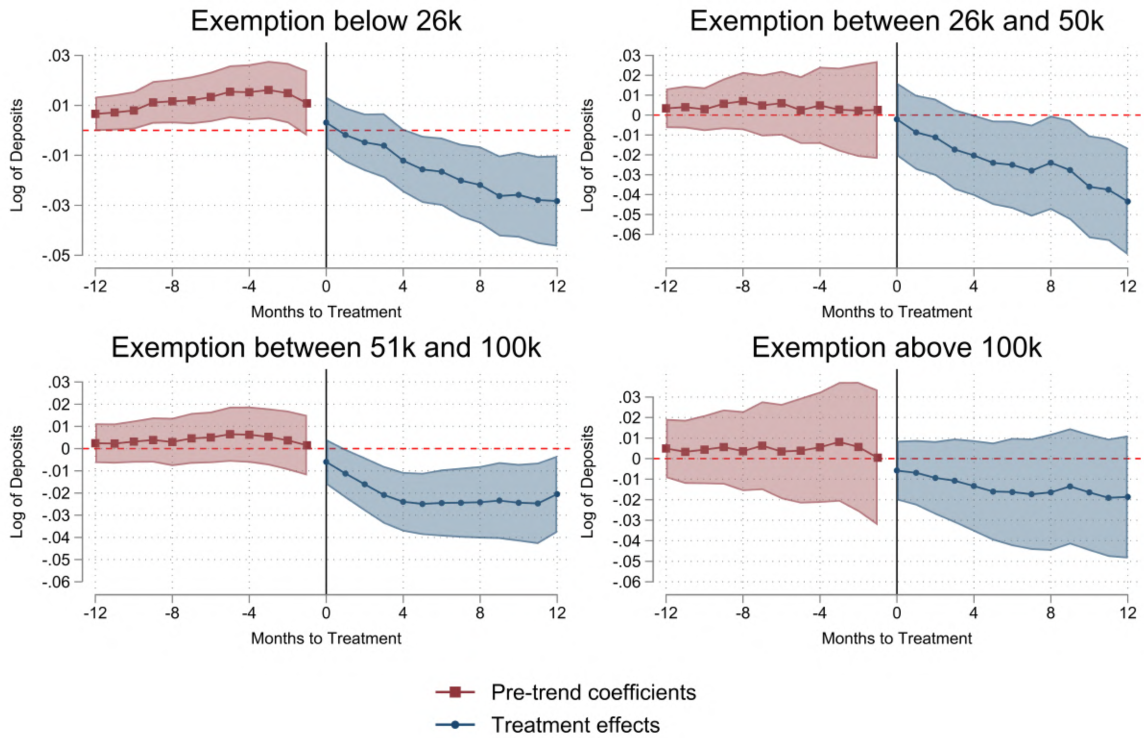

Figure 10: Event Study Plot of the Effects on Household Deposits by Exemption Thresholds. Results for this graph are obtained with the BJS estimator. Own illustration. Data source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA 1999-2022, used in 2022, 2023 and 2024, own calculations.

Deposit intensity. Heider et al. (2019) show that deposit intensive banks' net worth is relatively stronger negatively affected following the introduction of negative policy rates because their funding costs decrease relatively less due to the downward stickiness of deposit rates. According to this finding, the introduction of negative household deposit rates should have a relatively stronger positive effect on credit creation for more deposit intensive banks. Figure 17 in Appendix B shows that this is indeed the case. Banks below the fifth decile, when ranked according to their deposit intensity, do not experience a statistically significant increase in credit creation, while banks above the fifth decile do.

Savings deposits. As mentioned before, anecdotal evidence from the data collection process indicates that banks tried to convince their customers to invest their funds elsewhere with the bank after introducing negative household deposit rates. Figure 18 in Appendix B depicts the effects of the introduction of negative household deposit rates on savings deposits. It can be seen that there is a statistically significantly positive effect on savings deposits from eight months after the treatment onward. This increase is driven by the group of employed households and by savings deposits with an agreed period of notice of three months.

Sample split. When the first banks started to adopt negative household deposit rates in late 2019, it was sufficient to notify customers of the change in the terms of conditions of their deposit contracts. As a result of a legislative change, which became binding in April 2021 after a ruling of the German Federal Court of Justice, banks had to wait for their customers' approval in order to charge them with negative interest rates on their household deposits. I exploit this legislative change by splitting the sample in a way that treatment effects are estimated separately for NIR-banks that introduced negative rates before and after the ruling. Figure 19 in Appendix B shows that banks, which introduced negative household deposit rates before April 2021, experienced a stronger reduction in their household deposits compared to later treated banks.

Intensive margin. So far, the estimated effects have been based on methods focusing on the extensive margin of the treatment, i.e. the effects on banks that have introduced negative household deposit rates versus banks that have not. The collection of data on exemption thresholds also allows to study the intensive margin of an increase of the exemption thresholds. However, these results should be interpreted with caution, since they require significantly stronger identifying assumptions. To be more precise, to compare treatment effects across banks with different exemption thresholds requires that banks with a higher exemption threshold would have experienced the same effects on the outcome variable as banks with lower exemption thresholds if they would adopted that same threshold (Callaway et al., 2024). This assumption would be violated if banks' selection into different treatment intensities, i.e. exemption thresholds, would be somehow correlated with the treatment effect on household deposits that they experienced.

Furthermore, the specific design of the current analysis limits the availability of suitable estimation techniques to study the intensive margin. I have decided to use the estimator proposed in De Chaisemartin and d'Haultfoeuille (2024), which allows for different treatment intensities that can decrease multiple times. This is important because some banks have lowered their exemption thresholds over time.

The event-study estimators depicted in Figure 20 in Appendix B are non-normalized event study estimates, which can be interpreted as the average effect across all switchers that have experienced their actual treatment rather than their period zero treatment for the respective event study horizon. The definition of a switcher includes all banks that have changed their treatment at least once, including the initial adoption of negative household deposit rates by banks.

The average effect across all switchers is very similar to the estimates obtained in the main results section, which is most likely driven by the fact that the majority of NIR-banks introduced negative household deposit rates once and has not changed its exemption threshold afterwards, meaning that the average across all these banks is very similar to the baseline estimates.

Bank type for loans. In line with the results for household deposits, only public banks and credit cooperatives exhibit an increase in credit creation. The group of other banks experiences a decrease in credit creation, which becomes statistically significant only eight months after treatment. Again, the small sample of the subgroup of "Other Banks" drives this result. The result is graphically depicted in Figure 21 in Appendix B.

4 Robustness

Regional disparities. One potential concern regarding the validity of the results is that they are driven by regional clusters in specific states. To alleviate these concerns, Figure 11 depicts the effect of the introduction of negative policy rates on household deposits, where each line represents an estimation in which one state has been dropped from the sample. The confidence intervals are omitted for clarity. It can be seen that there is next to no variation in the treatment effects across the different samples, even though the geographical distribution of NIR-banks is quite uneven. This indicates that there are no regional differences in treatment effects that might cause any biases for the aggregate treatment effect. It has also been checked that treatment assignment is neither regionally clustered, nor by region-bank type.[13]

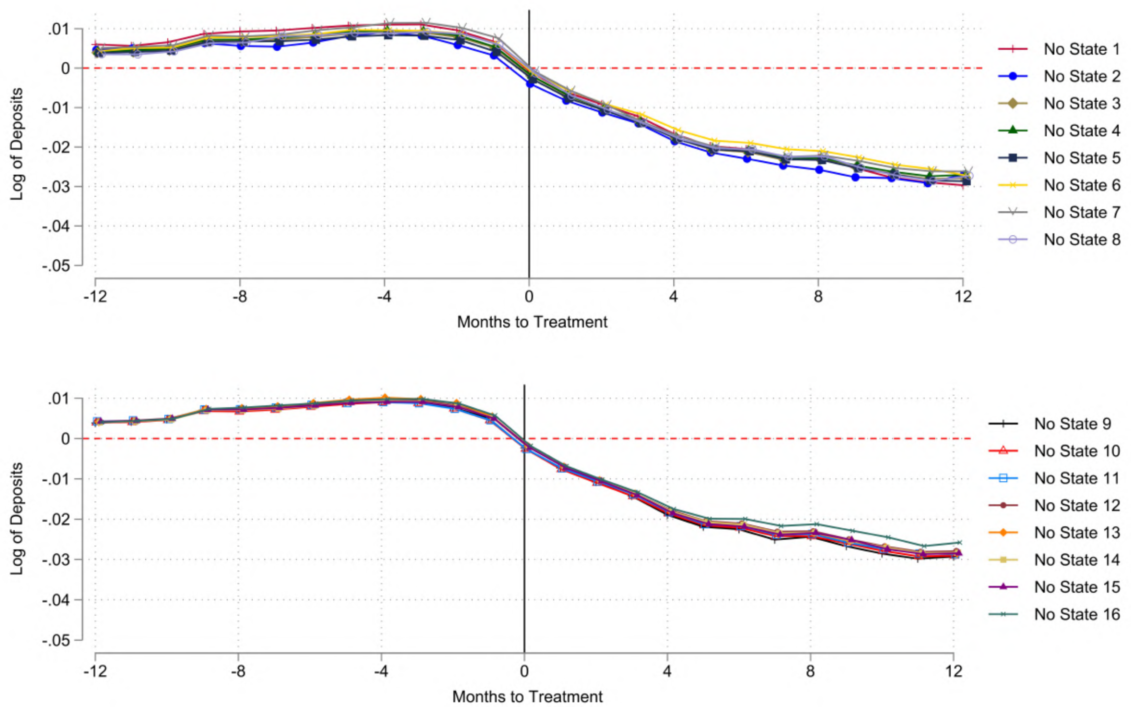

Figure 11: Leave One Out Exercise with States
This graph shows a leave-one.out exercise with states. Each regression line represents a regression to estimate treatment effects, leaving out one state each time. Results are obtained with the BJS estimator. Own illustration. Data source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA 1999-2022, used in 2022, 2023 and 2024, own calculations.

[13] An animated graph which shows the geographical distribution of NIR-banks by month of the introduction and bank type is available upon request from the author. This animated graph shows no evidence of regional clustering.

Placebo tests. As an additional robustness check a placebo exercise is conducted, using deposits of the domestic general government and foreign non-banks as outcome variables. Since negative deposit rates have only been introduced on household deposits, these variables should have remained unaffected by their introduction. This rules out that time-varying factors, which affect deposits in general and have not been picked up by the fixed effects, are driving the main results. Figure 12 shows that this is indeed the case. None of the post-treatment coefficients for either variable are statistically different from zero.

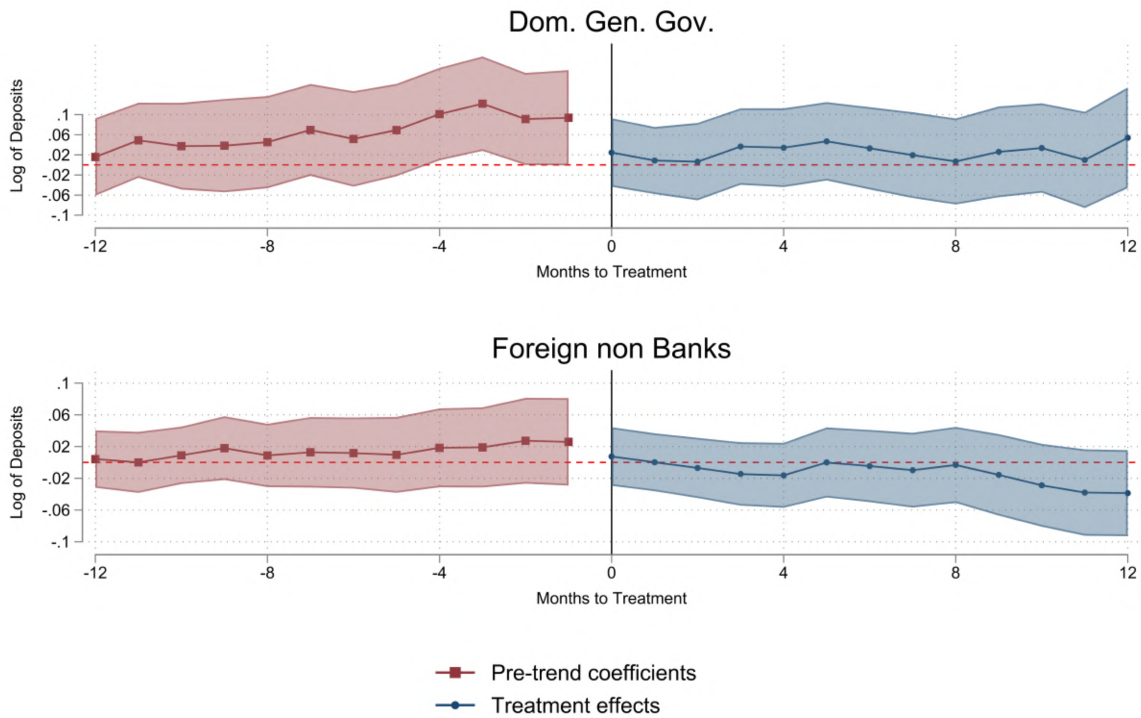

Figure 12: Event Study Plot of the Effects on Deposits of Domestic General Government and Foreign non-Banks.
Results are obtained with the BJS estimator. Own illustration. Data source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA 1999-2022, used in 2022, 2023 and 2024, own calculations.

Alternative control group. One potential objection to the empirical analysis is that non-NIR-banks do not provide a suitable control group for NIR-banks, casting doubts over the accuracy of the estimation results. While I have already addressed these concerns by providing some descriptive statistics comparing the two groups and controlling for both time varying and invariant factors in the regression analysis, using only the not-yet treated NIR-banks as a control group is another robustness check to tackle this issue. This assumes that the evolution of household deposits of not-yet treated NIR-banks is better suited as a counterfactual for the evolution of the treated outcome variable. Figure 13 shows that the results of this robustness check are in line with the main results. Both the pre-trend coefficients and the treatment effects are a bit more erratic than in Figure 5, which is due to the smaller sample size of the control group when using only the not-yet treated.

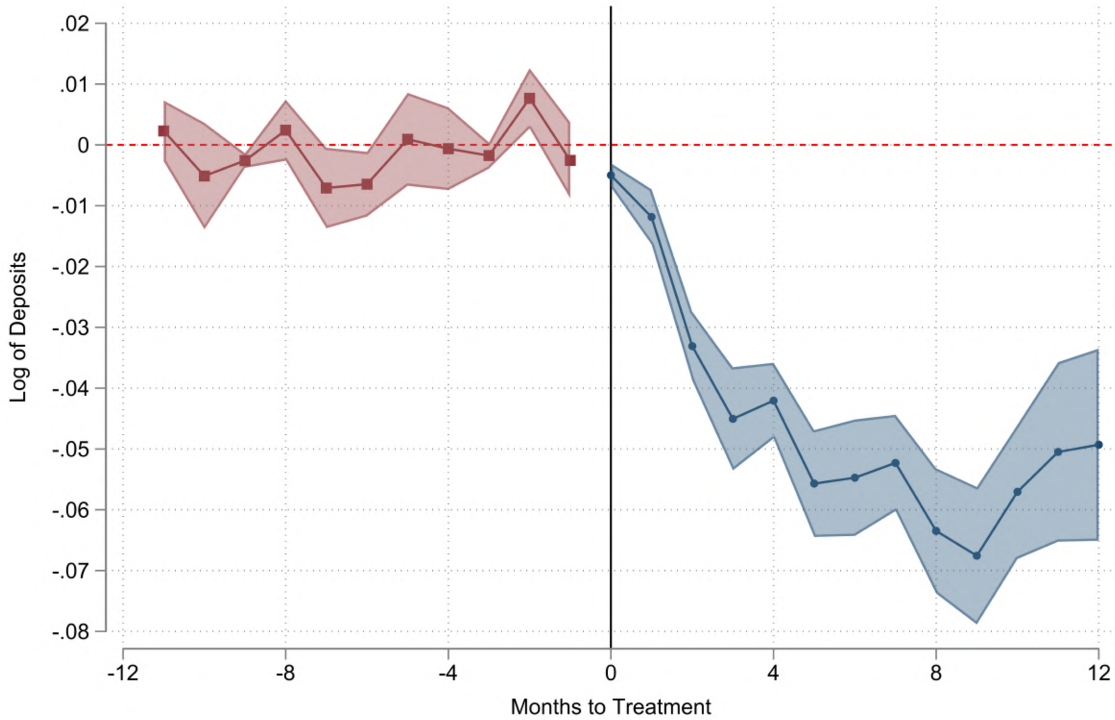

Figure 13: Event Study Plot of Effects on Household Deposits using only Not-Yet Treated Banks as Control Group
Results obtained withe CS estimator. Own illustration. Data source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA 1999-2022, used in 2022, 2023 and 2024, own calculations.

5 Conclusion

In this paper, I present novel evidence that the zero lower bound on household deposit rates is not as binding as previously thought. Between May 2019 and April 2022, a total of 483 German banks have introduced negative interest rates on household deposits. Concurrently, these banks introduced exemption thresholds, only above which the negative remuneration was applied. These thresholds are quite diverse, ranging from €0 to more than €500k.

In absolute terms, most NIR-banks are located in states in the Western part of Germany, while in relative terms more NIR-banks are located in the Eastern part of Germany. The vast majority of NIR-banks belongs to the groups of cooperative or public banks, while only 23 NIR-banks belong to other types of banks such as big or private banks. This finding is rooted in the structure of the German banking system. It is characterized by a large number of public and cooperative banks, which are usually smaller, operate locally and exhibit a strong reliance on deposit funding. These banks were disproportionately affected by the persistent negative policy rates and an increase in excess liquidity during the same time period. As a consequence, these banks introduced negative household deposit rates more frequently than banks with a different business structure.

The empirical study conducted in this paper uses a staggered DiD approach, for which treatment is defined as the staggered introduction of negative household deposit rates. Recent advancements in the literature are incorporated into the analysis, including diagnostic statistics by De Chaisemartin and d'Haultfoeuille (2020) and Goodman-Bacon (2021) as well as new estimation strategies Callaway and Sant'Anna (2021) and by Borusyak et al. (2023). The employed diagnostic statistics show that the problems associated with the TWFE regression approach in settings with staggered adoption of treatment and heterogeneous treatment effects are not of first order importance in the current analysis. As a consequence, the TWFE estimator is also used in the analysis to further assess the robustness of the results.

The main result of the paper is that the introduction of negative household deposit rates leads to a reduction of household deposits of up to three percentage points within twelve months after their adoption. The significant reduction in household deposits in spite of the sizable exemption limits indicates that rate cuts in negative territory are more salient than those in positive territory, giving rise to behavioral responses that are not present otherwise. Additionally, exemption thresholds might not have been believed to be credible by customers. Moreover, households' lower liquidity holdings and less-frequent needs to make large transactions should make it easier for them to substitute deposits for cash (see e.g., Brandao-Marques et al., 2021; Eisenshmidt & Smets, 2019).

Furthermore, I show that credit creation is positively affected by the introduction of negative household deposit rates. Depending on the estimation technique, household loans increase between one and two percentage points following the introduction of negative household deposit rates. One potential reason for this finding is that, besides reducing the amount of household deposits, increasing credit creation is another way for banks to reduce their excess reserve holdings at the central bank. Reducing these excess reserves, which were remunerated at a negative rate during that time, mitigates the burden due to punitive interest payments. Another potential mechanism is that some banks become financially less constrained after having introduced negative deposit rates, allowing them to increase credit creation (see e.g. Jiménez et al., 2012; Kashyap & Stein, 2000, for the effects of monetary policy on financially constraint banks). This is supported by anecdotal evidence obtained during the data collection process, according to which the reduction in household deposits was a desired outcome for these banks.

The positive effect on credit creation is evidence for an operative bank lending channel of monetary policy after banks decrease their household deposit rates below zero. Up to now, this channel has been considered as muted due to the perceived zero-lower bound of household deposit rates. This finding complements already existing contributions on the implications of negative policy rates and negative corporate deposit rates for monetary policy.

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6 Appendix A

6.1 Additional Information on the Data and Terminology

The self-collected data set is the core element for the empirical analysis conducted in this paper. It contains detailed information on banks that have introduced a negative remuneration on deposits held by households. The information on NIR-banks recorded in the self-collected data set consists of the name of the bank, the rate of remuneration, the date of introduction and abolition of negative deposit rates as well as details on the exemption limits, above which the negative remuneration applied.

The basis for the data set on NIR-banks was collected from the price comparison websites Verivox and Biallo, which kept a record of banks that have introduced negative deposit rates. For most of these banks, the interest rate and exemption limits were listed as well. While the information provided on interest rates was very accurate, this was not the case for the exemption limits. In many cases, information on these limits was incomplete or missing altogether.[14] This initial list of NIR-banks from the aforementioned websites was complemented with additional NIR-banks gathered from other websites and newspaper articles.

This rudimentary data set on NIR-banks was amended by self-collected data on the date of the first adoption of negative household deposit rates, the date of their abolishment and more details on exemption limits. The collection process for this additional data consisted of four main steps. In the first step, all available information was collected from the banks' websites. In most cases, the information was only available in the so-called 'Preisaushang' or 'Preis- und Leistungsverzeichnis', which are documents in which the bank lists prices and conditions for its products. Albeit these documents are the most comprehensive ones that are publicly available, in many cases information on the date of the first introduction of negative household deposit rates was missing. As a second step, all banks, for which no information was available on their websites, were contacted by mail. Then, all remaining banks, for which no information has been successfully collected yet, were contacted by phone. Last but not least, the so-called Wayback Machine was used to browse archived versions of banks' websites. All steps of the collection process were conducted in a standardized manner.[15]

In the end, data on the date of the first introduction of negative household deposit rates was successfully collected for 341 of 483 banks that have introduced them. Out

[14] Incompleteness could happen because several banks have changed their exemption limits over time, sometimes even more than once.

[15] The research interest and academic affiliation of the author was specified right at the beginning of any interaction. Afterwards, all banks received identical questions in both the mails and phone calls.

of the missing 142 banks, 68 actively refused to cooperate, 48 were not able to provide a definite answer and 26 have not responded at all.

In the final data set, the self-collected data is merged with data sets provided by the Research Data and Service Centre (RDSC) of the German Bundesbank. The final data set has a monthly frequency and runs from May 2018 to June 2022. The data sets provided by the RDSC consist of the balance sheet statistics (BISTA), selected master data for monetary financial institutions (MaMFI) and the banks' profit and loss accounts (GuV).[16] The BISTA is recorded at a monthly frequency and contains domestic banks' assets and liabilities based on the books at the end of the month. All balance sheet items are recorded at the bank, but not an individual level. The BISTA only records the domestic part of a bank's business, while the international activities of banks are excluded. The BISTA comprises of the main form and several annexes, in which balance sheet items are broken down by type, term, debtor and borrower sector.

The MaMFI contains information on the category to which a bank belongs, the type of institute, its location and some information on bank exit, mergers and acquisitions.

The GuV is recorded yearly and contains data on the income and expenditure of MFIs, including the evaluation of profits and losses calculated from the annual accounts as well as profit and loss statistics based on yearly averages from the BISTA. Opposed to the BISTA, the GuV also includes profits and losses generated from international business activities.

6.2 The German Banking System

The German banking system is build upon a so-called three pillar system, consisting of private banks, cooperative banks and public banks, which again can be divided into subcategories. Private banks are legally and economically independent and operate under the objective of profit maximization. Most notably, this sector comprises the biggest German banks as well as some regional and other commercial banks.

Cooperative banks are characterized by a special legal form, in which customers can acquire shares of the respective bank. Credit cooperatives are usually smaller banks that operate regionally with the objective to support their customers in the best possible way. The biggest subgroup of cooperative banks are the 'Volks- und Raiffeisenbanken'.

Public banks, which represent the third pillar of the German banking system, are

[16] More information on the data sets can be found here:
Monthly balance sheet statistics DOI: 10.12757/BBk.BISTA.99Q1-22Q4.01.01
Banks' profit and loss statements DOI: 10.12757/BBk.GuV.9922.01.01
Selected master data for MFIs DOI: 10.12757/BBk.MaMFI.199901-202212.01.01

predominantly owned and financed by public entities, such as cities and other municipalities. They operate under the regional principle, according to which they only do business within the region of their ownership. Their activities are focused around the traditional banking services of taking deposits and providing loans. The most important subgroup of public banks are the Sparkassen, followed by Landesbanken.[17]

An important characteristic of the German banking system is the prevalence of the so-called house bank principle (Harhoff & Körting, 1998). This principle refers to the fact that, for many banks, profit maximization is not the primary objective. This is especially true for smaller banks and banks from the second and third pillar of the banking system. According to this principle, banks primary objective is to ensure the long-term financial success of their customers. This different focus results in a stronger relationship between banks and their customers, which has consequences for the banking system. It can either lead to more favorable borrowing and lending conditions even in dire economic circumstances, but also to more market power for banks. This can affect the reaction of a bank's customers following a policy change, such as the introduction of negative deposit rates. Presumably, the stronger bank-customer relationship makes customers more lenient with respect to a change in conditions, increasing the likelihood of staying at the bank after the introduction of negative deposit rates. This alleviates concerns for local spillover effects in the estimation process later on. Additionally, anecdotal evidence obtained during the data collection process suggests that banks tried to convince customers to stay with the bank after the introduction of negative deposit rates. NIR-banks motivated their customers to invest their funds held in deposit accounts into other products with the same bank.

6.3 Additional Comments on the Empirical Strategy

This section gives a more detailed account of the estimation strategy.

Treatment is defined as the staggered introduction of negative household deposit rates by banks and modeled as a binary variable, taking on values of either zero or one.[18] In the current setting, treatment is an absorbing state, meaning that no bank that has introduced negative household deposit rates abolished them during the period of study. Moreover, the introduction of negative household deposit rates is endogenous because, contrary to a change in policy rates, banks decide themselves whether to introduce negative rates. In such a setting, the most commonly used method is difference-in-

[17] For a more in-depth analysis of the German banking system, see (Urbschat, 2018)

[18] Theoretically, the availability of data on exemption limits also allows for a continuous treatment design. However, in that case the sample would be significantly smaller since data on exemption limits has not been available for all NIR-banks for which the date of introduction was collected.

differences.

Assuming that the timing of treatment is independent to bank-specific and time-specific fixed effects, treatment effects can be estimated in a DiD model which can be described by the following equation:

$$y_{i,t} = \alpha_i + \lambda_t + \sum_{k=-K}^{-2} \beta_k^{lead} D_{i,t}^k + \sum_{k=0}^{L} \beta_k^{lag} D_{i,t}^k + \theta X_{i,t} + \epsilon_{i,t}, \tag{1}$$

where α_i and λ_t denote unit and time period fixed effects, $X_{i,t}$ are time-varying covariates and β_k^{lag} depicts the treatment effect k periods after treatment, while β_k^{lead} denotes pre-trends. Equation (1) is an event-study specification, which can be estimated with ordinary least squares (OLS). Its estimator is commonly referred to as the two-way fixed effects (TWFE) estimator.

This approach has been used in numerous cases, including settings with a single or multiple treatment periods, dynamic or static as well as homogeneous or heterogeneous treatment effects. However, recent contributions have shown that estimators obtained by a TWFE regression specification are potentially biased in many of these cases. For example, Goodman-Bacon (2021) shows that the static treatment effect obtained by a TWFE regression is not per se interpretable as the average treatment effect on the treated (ATT). Sun and Abraham (2021) and De Chaisemartin and d'Haultfoeuille (2020) show that the estimated treatment effect might be biased in a setting with staggered treatment and treatment effect heterogeneity, even if one allows for dynamic treatment effects, as in (1).

The underlying reason for the arising biases is a problem of so-called 'bad comparisons' being included in the computation of the treatment effect. To be more precise, treatment effects obtained by the TWFE regression approach are variance-weighted averages of many 2x2 DiDs, in which the average change in the outcome variable of treated units is compared to the average change in the outcome variable of untreated units. In the unproblematic 2x2s, units from the treatment and comparison group are compared before and after units from the treatment group receive treatment. However, there are also problematic cases included in the computation, in which already treated units act as comparison units to later treated units. In this case, the difference between the effective comparison and later treated unit does not reflect the true treatment effect because the outcome change of the comparison unit over time might itself reflect a treatment effect. The consequence is that the estimated ATT might be different from the true one. In the extreme case, one might estimate a statistically significant ATT, while the true effect is equal to zero or of opposite sign.

I address the concerns associated with the TWFE estimator in a setting with staggered treatment by applying diagnostic statistics proposed by Goodman-Bacon (2021) and De Chaisemartin and d'Haultfoeuille (2020). The latter method computes the number of negative weights attached to 2x2's in the estimation process and informs the researcher whether the true treatment effect is potentially zero or of opposite sign to the estimated one. According to this approach, no negative weights are used in the computation of the ATT by the TWFE specification in this analysis. For the data generating process to be compatible with an ATT equal to 0, the individual treatment effects would need to have a standard deviation of 0.0811. For the empirical analysis in this paper, this implies that treatment effect heterogeneity would need to be implausibly large for the true ATT to be equal to 0.

The diagnostic statistic by Goodman-Bacon (2021) yields similar results, showing that more than 90% of the weight in the computation of the ATT are attached to entirely good 2x2 comparisons, in which never treated banks are compared to treated ones. The 10% of the weight attached to timing groups, which also include bad comparisons of earlier vs. later treated units, exhibit an ATT which is very similar to the one computed by the other 90%. The results from this decomposition are depicted graphically in Figure 16 in the Appendix B.

The results from the diagnostic statistics indicate that the problems associated with the TWFE estimator do not seem to be of first-order importance for this empirical analysis. Nevertheless, bad comparisons are still assigned some weight in the estimation process of the TWFE estimator and warrant some attention. As a consequence, additional estimation strategies that are robust to this issue are applied. To be more precise, the estimators by Callaway and Sant'Anna (2021), short *CS*, and Borusyak et al. (2023), short *BJS*, are chosen. On top of allowing for dynamic and heterogeneous treatment effects in a setting with staggered adoption of treatment, they allow for the incorporation of control variables to relax the unconditional parallel-trends assumption to a conditional one. This leads to the following key identifying assumption for this empirical study: conditional on unit and time fixed effects as well as observable control variables, changes in the amount of household deposits of banks that have not introduced negative household deposit rates provide a good counterfactual for changes in the amount of deposits that would have been observed in NIR-banks absent of treatment.[19]

While both the CS and BJS estimator allow for the inclusion of time-varying control variables, they differ slightly in how they incorporate them. The CS estimator uses base period covariates, which means that they are kept constant in post-treatment periods at the value of the period prior to the one in which the treatment occurred.

[19]After replacing household deposits by household loans, the same assumption holds for household loans as the dependent variable.

Opposed to that, the BJS estimator includes the whole time path of time-varying control variables, i.e. they are not kept constant in post-treatment periods. I have conducted a simulation exercise to test the differential treatment of time-varying covariates of the two estimation strategies. It is indeed the case that changes in post-treatment periods for time-varying covariates do not affect the CS estimator, while they change the estimated treatment effect of the BJS estimator.[20]

In the case that the control variables might be potentially affected by treatment, including time-varying control variables might lead to biased results. Caetano et al. (2022) show that in such a case, it is sufficient to condition on pre-treatment values of time-varying covariates if the covariates evolve similarly between treated and control units that have the same time-invariant covariates and the same pre-treatment time-varying covariates. Hence, if the researcher is not convinced by the exogeneity of the included control variables, the estimator by Callaway and Sant'Anna (2021) should be applied and results based on the BJS estimator should be taken with caution.

In the current setting with household deposits (or subgroups of it) as the main outcome variable, loans are included as a time-varying control variable. The reason is that a change in credit creation also affects the amount of bank deposits from a balance sheet perspective. For example, comparing a bank in the treatment group to a bank in the control group that experiences an increase in credit creation would mean that the treated bank also experiences a relatively stronger increase in its deposits. Even if most of the newly created loans are used for various endeavors and are not kept at the bank, at least a small fraction of these loans will still be held as bank deposits. In such a case, comparing banks between the treatment and control group that follow different trajectories in creation would result in estimating a treatment effect that may be potentially obscured by differential trends in deposits due to differences in credit creation.

Additionally, the CS and BJS estimator differ in the strictness at which they make use of the conditional parallel trends assumption. CS only imposes only post-treatment parallel trends, while BJS imposes it for all groups and time periods. In other words, BJS uses the average of all pre-treatment periods as a comparison for the treated outcome, while CS only uses the last pre-treatment period (Roth et al., 2023). This difference comes with a trade-off. On the one hand, using all pre-treatment periods can increase efficiency (Wooldridge, 2021). On the other hand, if the (conditional) parallel trends assumption does not hold exactly, relying on a longer time horizon of pre-treatment observations increases a potential bias. Consequently, which estimator is preferable depends strongly on the application.

[20]If you are interested in the results of this simulation exercise, feel free to contact me.

Based on the preceding discussion, both estimators are applicable from a theoretical standpoint, although the CS estimator is slightly preferable for two reasons. First, it is more robust with respect to potential endogeneity concerns related to the included control variables because it only includes base period values. Second, the weaker parallel trend assumption that is imposed in the estimation process of the CS estimator reduces a potential bias if this assumption does not hold exactly. Nevertheless, both the CS and BJS as well as the TWFE estimator are used to assess the robustness of the main result.

Since the estimators by Callaway and Sant'Anna (2021) and Borusyak et al. (2023) have only been recently proposed, they are discussed in a bit more detail. The CS estimator is build upon a particular disaggregation of the overall treatment effect, namely the group-time average treatment effect. The group-time average treatment effect is defined as the treatment effect for group g at time t, where a group is defined as a cohort of units first treated at time g. This effect is denoted in a potential outcomes framework by

$$ATT(g,t) = \mathbb{E}[Y_t(g) - Y_t(0)|G_g = 1].$$

The unit subscripts are omitted for clarity. $Y_t(g)$ denotes the actual outcome of units at time t, treated at time g, while $Y_t(0)$ denotes their potential outcome. The group-time effect parameters can then be used to compute more aggregated ones, for example event study parameters where group-time effects are aggregated for each event horizon e and weighted accordingly:

$$\beta_{es}(e) = \sum_{g \in G} \underbrace{\mathbf{1}\{g+e \leq T\}\mathbf{1}\{t-g=e\}P\{G=g|G+e \leq T\}}_{w(g,t)} ATT(g, g+e) \tag{2}$$

Here, $\beta_{es}(1)$ is the average treatment effect across all groups g one time period after their respective treatment. The weight for each group and time horizon, $w(g,t)$, includes indicator functions that only consider identified group-time average treatment effects. The last component of the weight, given by $P\{G = g|G + e \leq T\}$, specifies the summation method. In this case, groups are weighted by their respective size.[21]

While the treatment effects in the dynamic TWFE specification are estimated by using OLS, Callaway and Sant'Anna (2021) show that the $ATT(g,t)$'s in their approach can be recovered by extending either an outcome regression procedure proposed

[21] With a staggered adoption of treatment, this aggregation method potentially suffers from compositional changes across event horizons unless one imposes very strong assumptions on treatment effect dynamics (Callaway & Sant'Anna, 2021). A potential solution is to only include balanced groups, i.e. only banks that have been treated e' periods. In the current setting, this is not very appealing because a significant fraction of the treatment group would be lost.

by Heckman et al. (1997) and Heckman et al. (1998), inverse probability weighting by Abadie (2005) or doubly robust estimands by Sant'Anna and Zhao (2020) to a framework with multiple groups and multiple time periods.

For the outcome regression approach to yield a consistent estimate for the ATT, the outcome model used to estimate the conditional expectation function of the evolution of the control group needs to be correctly specified. On the other hand, the inverse probability weighting approach relies on a correct specification of the propensity score, which is defined as the conditional probability of unit i belonging to the treatment group g, given its pre-treatment covariates X. The doubly robust estimation approach combines the two aforementioned approaches and requires either the outcome model of the conditional expectation function or the propensity score to be correctly specified. In this sense, the doubly robust estimation is more forgiving with respect to misspecifications. Due to these advantages compared to other estimation techniques, the results in this paper based on the CS estimator are computed using the doubly robust estimation technique. The estimator for the group-time ATT is given by

$$ATT_{dr}^{ny}(g,t;\delta) = \mathbb{E}\left[\left(\frac{G_g}{\mathbb{E}[G_g]} - \frac{\frac{P_{g,t+\delta}(X)(1-D_{t+\delta})(1-G_g)}{1-P_{g,t+\delta}(X)}}{\mathbb{E}\left[\frac{P_{g,t+\delta}(X)(1-D_{t+\delta})(1-G_g)}{1-P_{g,t+\delta}(X)}\right]}\right)\left(Y_t - Y_{g-\delta-1} - m_{g,t,\delta}^{ny}(X)\right)\right] \tag{3}$$

where $m_{g,t,\delta}^{ny}(X) = \mathbb{E}[Y_t - Y_{g-\delta-1}|X, D_{t+\delta} = 0, G_g = 0]$ is the population outcome regression using the not-yet treated as a control group. δ is the anticipation horizon, i.e. by how many periods units anticipate the treatment, and $P_{g,t+\delta}(X)$ denotes the propensity score for a given group and event horizon.[22]

The BJS estimator by Borusyak et al. (2023) belongs to the class of imputation estimators. The procedure for this estimator can be quite easily explained. In the first step, the outcome for non-treated units is estimated by a TWFE regression which includes only units and time periods that have not yet been treated: $Y_{i,t} = \alpha_i + \lambda_t + \theta X_{i,t} + \epsilon_{i,t}$ Then, the fitted values from this regression are used to impute the potential non-treated outcome for treated units, given by $\hat{Y}_{i,t}(0)$. The treatment effect for each treated unit can then be computed as the difference between the actual outcome and the potential non-treated outcome for treated units, $Y_{i,t}(1) - \hat{Y}_{i,t}(0)$, which can then be aggregated to obtain the estimands of interest.

In general, for the results from the different estimation techniques to yield consistent estimates of the true ATT, a few essential assumptions have to be satisfied. First

[22]In the current setting δ is assumed to be zero, i.e. there is no treatment anticipation.

of all, treatment has to be irreversible.[23] Secondly, it is assumed that the sample under study consists of i.i.d draws from a population. Thirdly, the overlap assumption states that there is a positive fraction of units receiving treatment in period g and that the conditional probability of belonging to the treatment group, given the observed covariates, is bounded away from one. In other words, this assumption rules out issues arising due to irregular identification.

Another important assumption is that there is no (or only limited) treatment anticipation.[24] This means that treatment in period t has no effect on the outcome variable prior to treatment. For the empirical study in this paper, this means that household deposits of NIR-banks must not have been affected by negative household deposit rates prior to their introduction. This is very likely to be satisfied because, while banks themselves have made the decision to introduce negative deposit rates, its the customers' reaction to the introduction which leads to a change in deposits. There is no indication that customers have reacted before the negative remuneration has been actually introduced.[25] From a theoretical point, both the CS and BJS estimator also hold under limited treatment anticipation as long as it is accounted for.

[23]Some recent contributions show how to deal with reversible treatments. See e.g. Viviano and Bradic (2021) for incorporating sequential ignorability into economic analysis.

[24]In the case of no anticipation, $\delta = 0$ from Equation (3) in Appendix A.

[25]Before April 2021, customers only had to be notified after negative household deposit rates were introduced. After April 2021, banks had to inform their customers and wait for their approval before charging negative deposit rates. Nevertheless, there is no indication that customers would have had an incentive to shift their funds prior to the actual start of the negative remuneration.

7 Appendix B

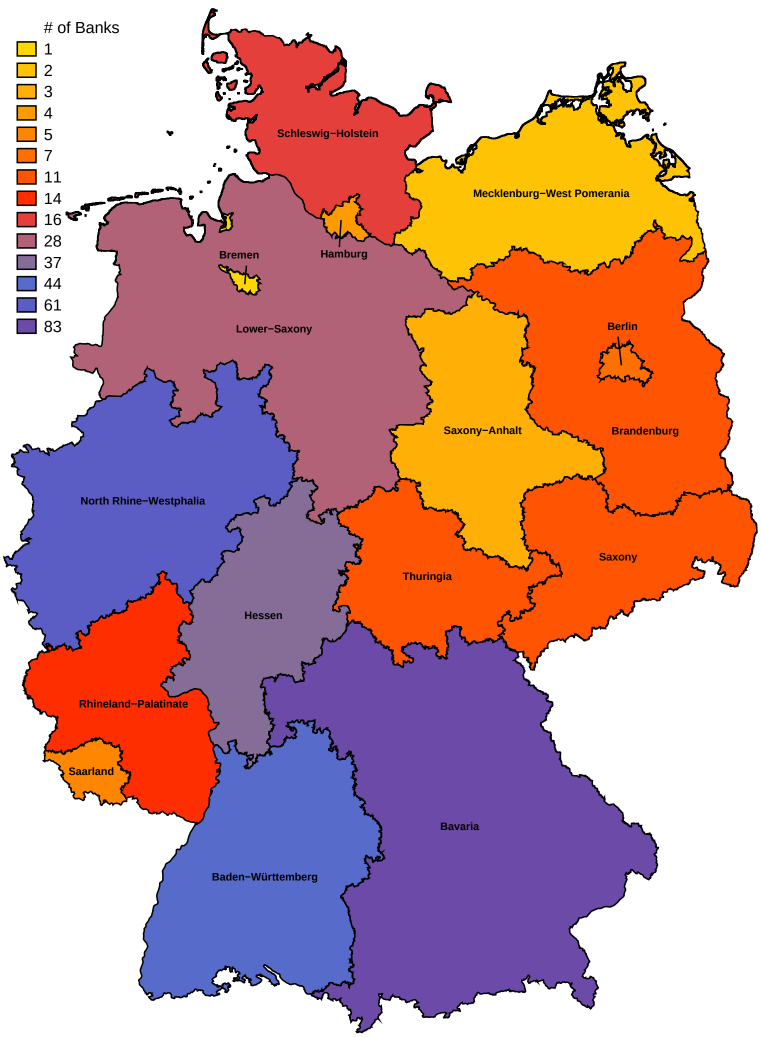

Figure 14: Geographical Distribution of NIR-Banks in Germany with Date of Introduction. This figure shows the geographical distribution of all NIR-banks in Germany, for which the date of introduction was successfully collected. The location is determined based on the official location of a banks' headquarter. Own illustration. Data source: self-collected dataset.

Table 1: Statistics For Bank Balance Sheet Variables

		05/2018						06/2022					
		N	*Mean*	*P25*	*P50*	*P75*	*SD*	*N*	*Mean*	*P25*	*P50*	*P75*	*SD*
NIR = 0	*Deposits (all dom. HH)*	627	441590	63776	196126	537044	813469	627	627800	97997	2785617	775707	1107072
	Deposits (econ. ind. HH)	626	71114	11043	34803	89236	103536	626	100573	17531	49165	133731	135175
	Deposits (emp. HH)	626	324098	45165	133069	381713	670467	626	472412	69186	204820	572777	928091
	Deposits (other HH)	627	47007	6188	15454	46092	126355	625	55907	7293	20254	56909	139353
	Deposits (gen. Gov.)	584	23306	1329	5446	21232	81405	584	33686	1592	6690	35704	66117
	Deposits (for. non-banks)	619	12894	481	1795	7278	83579	621	24532	576	2201	8511	220418
	Loans (all HH)	627	598039	98524	267321	707622	1247502	627	717109	125570	336157	897815	1298738
	Saving Deposits (all HH)	627	289975	46790	141737	375687	416611	627	276645	45530	131558	355521	396765
	Total Assets	627	1579397	208265	653071	1712560	3989032	627	1885403	271662	807678	2159761	3769763
NIR = 1	*Deposits (all dom. HH)*	283	1813683	175813	416646	1179250	7576178	283	2438751	254730	591152	1622184	8956252
	Deposits (econ. ind. HH)	283	315125	31333	75270	179764	1201430	283	424513	46063	105015	269149	1551336
	Deposits (emp. HH)	283	1250059	120458	294027	888521	4854204	283	1779532	174902	448695	1247821	6649780
	Deposits (other HH)	283	248499	14172	38364	111814	1912426	283	234706	17152	51378	133335	1177139
	Deposits (gen. Gov.)	272	65552	2755	10391	39658	317897	274	117307	3557	15815	62246	688441
	Deposits (for. non-banks)	283	97031	1194	4311	15892	959166	283	110821	1527	5179	19106	1025358
	Loans (all HH)	283	1659928	198290	538086	1380859	5469635	283	2033852	281710	673683	1757803	6741036
	Saving Deposits (all HH)	283	591029	96388	283773	713633	1049929	283	563672	93238	270062	663298	1063359
	Total Assets	283	5689574	491290	1331970	3425705	26197375	283	7848407	639526	1679469	4399526	40058664
Total	*Deposits (all dom. HH)*	910	868296	85094	258222	646355	4320457	910	1190986	126875	393834	914934	5141259
	Deposits (econ. ind. HH)	909	147082	14627	46121	107454	684434	909	201426	23085	65251	157563	884612
	Deposits (emp. HH)	909	612379	59565	181038	472563	2794919	909	879359	92274	282256	690529	3833146
	Deposits (other HH)	910	109669	7949	21992	63464	1074400	908	111634	9842	28276	76420	671601
	Deposits (gen. Gov.)	856	36730	1602	6974	24668	192191	858	60391	1904	8611	40783	394302
	Deposits (for. non-banks)	902	39292	632	2542	9296	542461	904	51545	801.5	3110	10948	602737
	Loans (all HH)	910	928275	117492	352740	832032	3254963	910	1126601	147496	450960	1034044	3953593
	Saving Deposits (all HH)	910	383600	56278	173993	436718	693508	910	365907	54648	179073	401817	690560
	Total Assets	910	2857617	272119	826650	1978017	15082922	910	3739832	347362	1077048	2542996	22698917

Deposits are defined in the BISTA as liabilities other than savings deposits- overnight money. Deposits are broken down into various subcategories, with the most relevant one for this paper being domestic households. Domestic households are again broken down into economically independent (self-employed), employed (wage and salary earners, including pensioners and unemployed) and other (housewives, infants, students etc.) households. Deposits (gen. Gov.) *depicts deposits held by the general government, while* Deposits (for. non-banks) *reports deposits held by foreign non-banks. These items will be used for robustness checks.*

Loans (all HH) *reports loans and advances of all domestic households and all maturities.* Saving Deposits (all HH) *reports savings deposits of all domestic households and all agreed period of notices.*

Note: The reporting universe comprises all domestic German banks (MFIs) with the status of deposit-taking institutions. The values, except for the number of banks, are reported in units of €1000, recorded by the end of the month and are rounded to the nearest integer.

Data Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA 1999-2022, used in 2022 and 2023, own calculations.

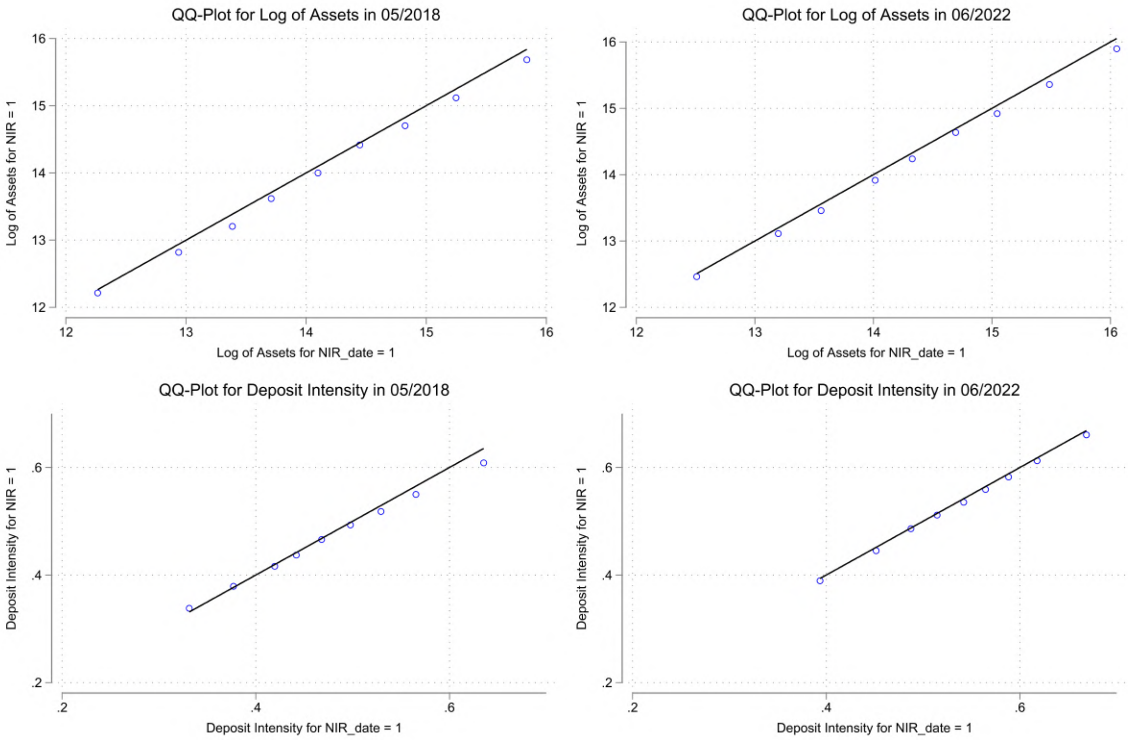

Figure 15: Quantile-Quantile Plots.
This graph depicts quantile-quantile plots comparing bank Size (top panels) and deposit Intensity (bottom panels) for NIR-Banks with and without the date of introduction in 05/2018 and 06/2022. Own Illustration. Data source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA 1999-2022, used in 2022, 2023 and 2024, own calculations.

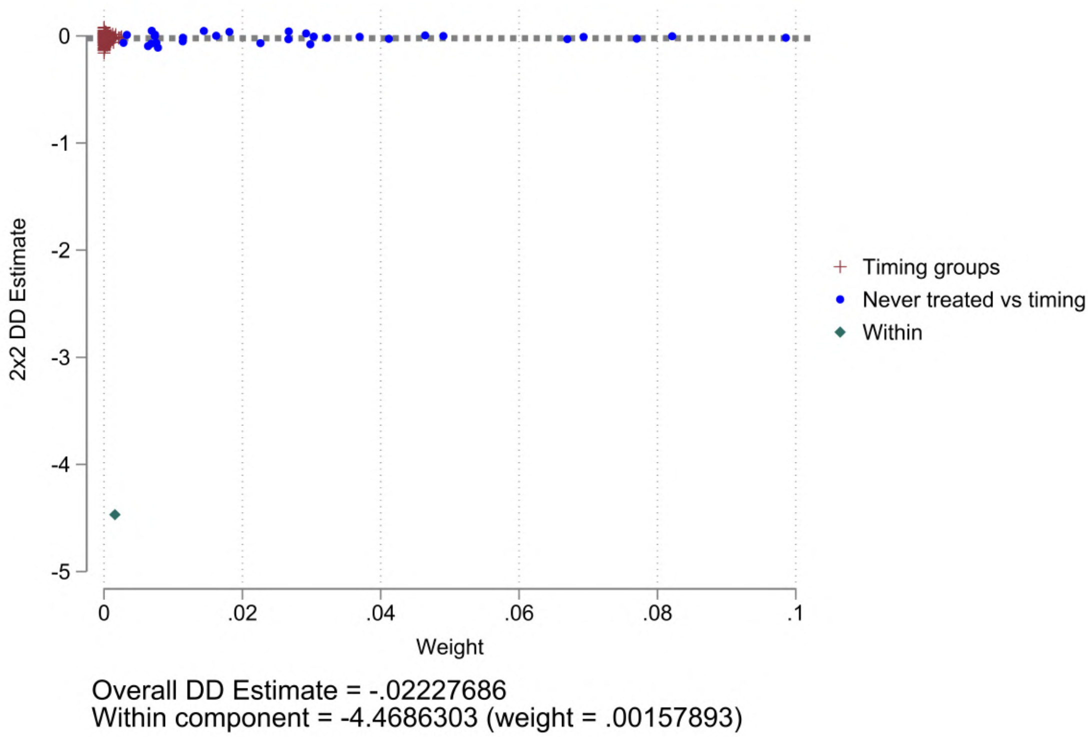

Figure 16: Graphical Representation of the Bacon Decomposition.
'Timing groups' refers to comparisons between earlier and later treated units. 'Never treated vs timing' refers to comparisons between never-treated and treated units. 'Within' refers to the within component of the estimator, which gives an idea about the variation due to the inclusion of control variables. Own Illustration. Data source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA 1999-2022, used in 2022, 2023 and 2024, own calculations.

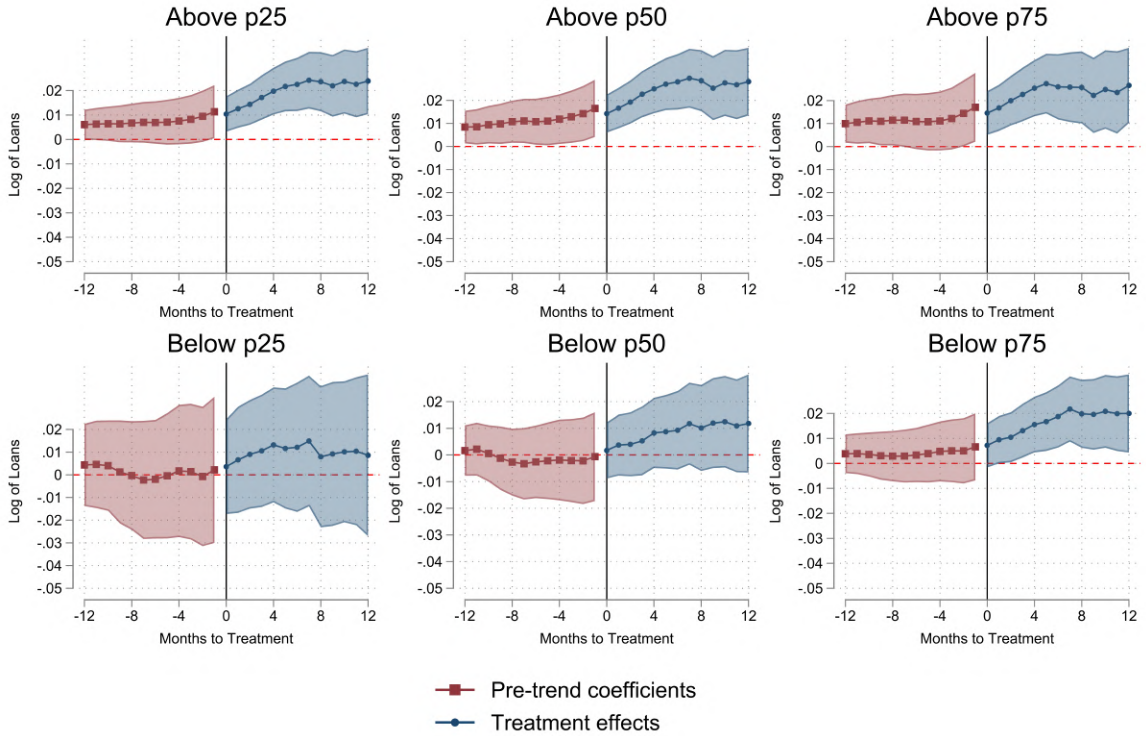

Figure 17: Event Study Plot of the Effects on Household Loans by Deposit Intensity. Deposit Intensity is defined as deposits over total assets. Results are obtained with the BJS estimator. Own illustration. Data source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA 1999-2022, used in 2022, 2023 and 2024, own calculations.

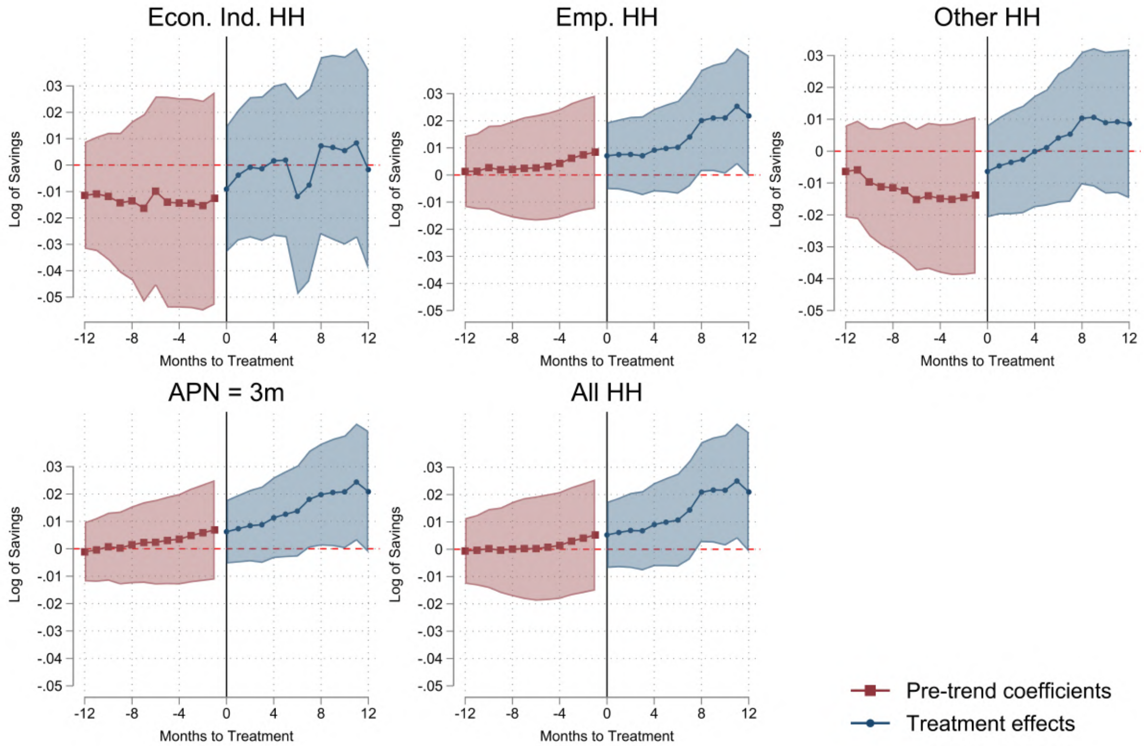

Figure 18: Event Study Plot of the Effects on Household Savings Deposits.
Savings are broken down by household type and the agreed period of notice. Results are obtained with the BJS estimator. Own illustration. Data source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA 1999-2022, used in 2022, 2023 and 2024, own calculations.

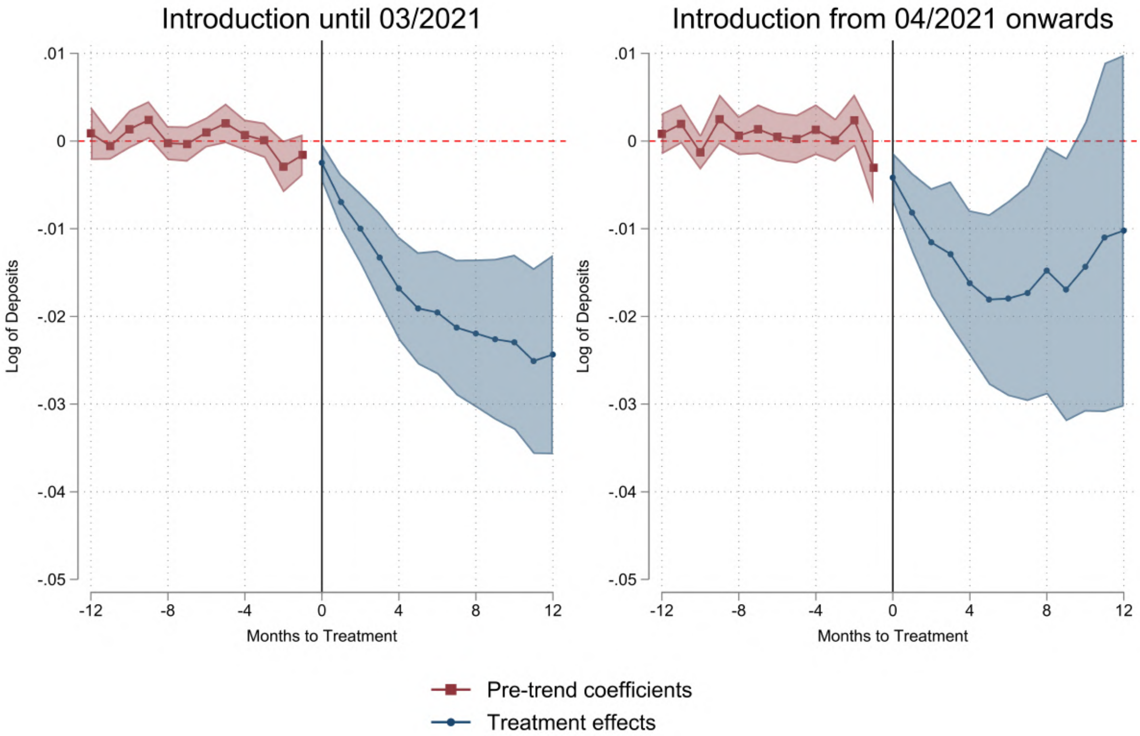

Figure 19: Event Study Plot of the Effects on Household Deposits with Sample Split.
Results for this graph are obtained with the CS estimator. Own illustration. Data source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA 1999-2022, used in 2022, 2023 and 2024, own calculations.

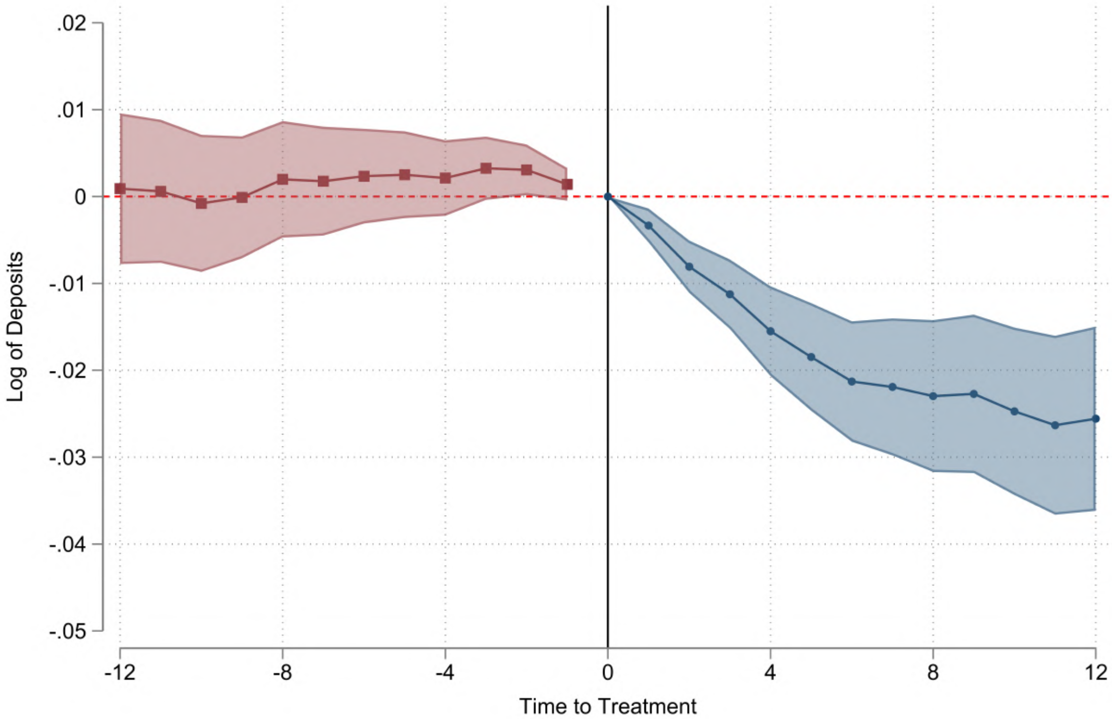

Figure 20: Event Study Plot of the Effects on Household Deposits at the Intensive Margin. The depicted coefficients are the non-normalized event study estimates as defined in De Chaisemartin and d'Haultfoeuille (2024). Own illustration. Data source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA 1999-2022, used in 2022, 2023 and 2024, own calculations.

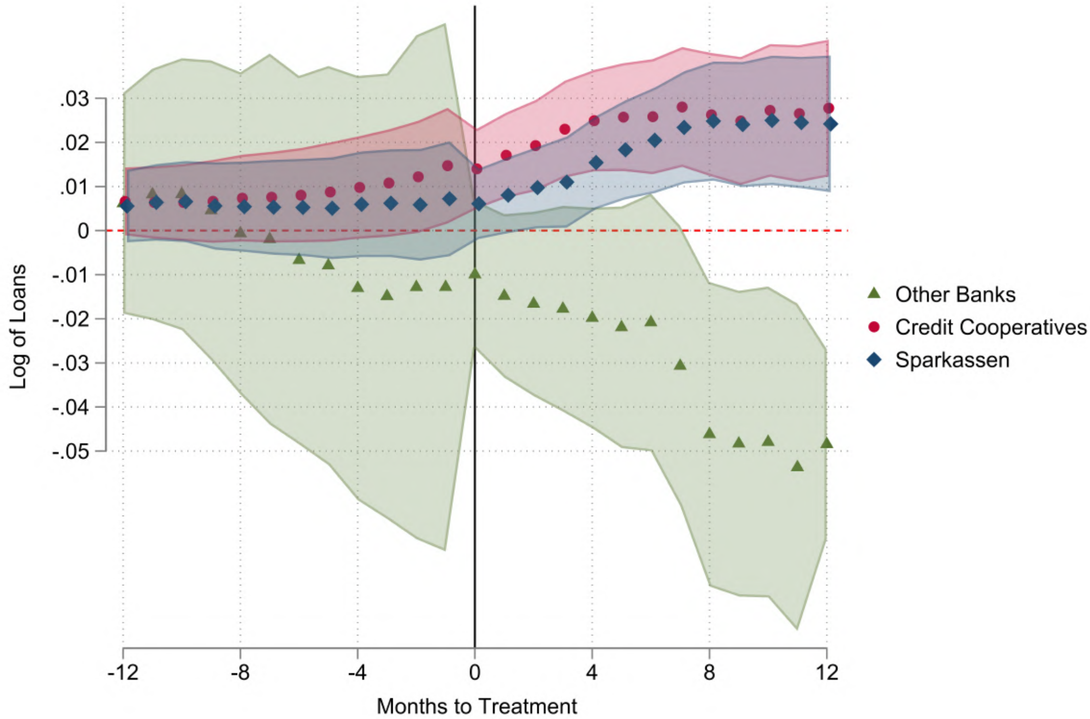

Figure 21: Event Study Plot of the Effect on Loans of Subcategories of Domestic Households. Results for this graph are obtained with the BJS estimator. Own illustration. Data source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA 1999-2022, used in 2022, 2023 and 2024, own calculations.