

Cross-Border Bank Flows, Regional Household Credit Booms and Bank Risk-Taking*

Dominik Boddin[†] Daniel Marcel te Kaat[‡] Kasper Roszbach[§]

December 17, 2024

Abstract

This paper provides novel micro-level evidence that cross-border bank flows are important for households' access to credit not only in emerging markets but also in advanced economies. These foreign bank flows can drive local credit credit booms that increase bank risk. We study how the influx of cross-border bank funding that followed the ECB's implementation of non-conventional monetary policy in 2014/15 impacted lending to households, using supervisory bank-level data alongside household-level credit and consumption data from Germany. Regional banks that are highly exposed to fluctuations in foreign capital inflows increase consumer lending to riskier, lower-income households by 50% more than other banks. When deposit inflows from non-euro area banks rise, this induces less capitalized banks to expand their lending on the extensive margin. Improved access to credit enables lower-income customers of exposed banks to increase non-durable consumer spending. Data from a larger group of euro area countries confirm our conclusions.

Keywords: Cross-Border Bank Flows, Households, Bank Lending, Risk-Taking, Credit Booms, Funding Shocks

JEL Classifications: F3, G2, G5

*This paper should not be reported as representing the views of the Bundesbank, Eurosystem or Norges Bank. The views expressed are those of the authors and do not necessarily reflect those of these institutions. We thank a referee for the Norges Bank working paper series, Tobias Berg, Nathan Converse, Valeriya Dinger, Linda Goldberg, Lars Norden, Steven Ongena, Tim Schmidt-Eisenlohr, Emil Verner and participants in the Norges Bank Spring Institute for valuable comments and Tobias Schmidt for sharing his code. This paper uses data from the Bundesbank Panel on Household Finances and the Eurosystem Household Finance and Consumption Survey, accessed via scientific use files. Reported results and related observations and analyses may not correspond to the results or analyses of the data producers. The confidential Bundesbank data was accessed at its Research Data and Service Centre via on-site use (Project No. 2023/0041). Te Kaat gratefully acknowledges financial support from the Dutch Research Council NWO, grant number VI.Veni.211E.023.

[†]Deutsche Bundesbank (dominik.boddin@bundesbank.de)

[‡]University of Groningen (d.m.te.kaat@rug.nl)

[§]Corresponding author: Norges Bank and University of Groningen (kasper.roszbach@norges-bank.no)

1 Introduction

An extensive body of literature has documented, using aggregate, bank-level, or bank-firm data that foreign capital inflows increase overall bank lending, with credit shifting towards riskier firms and countries (e.g., [Magud et al., 2014](#); [Baskaya et al., 2017](#); [Te Kaat, 2021](#)). Capital inflows resulting from changing national or international financial conditions affect bank lending through both securities and interbank markets as well as intra-concern flows in large global banks ([Cetorelli and Goldberg, 2012](#); [Temesvary et al., 2018](#); [Correa et al., 2021](#)). Such wholesale sources of foreign bank funding are known to be important in developing and emerging economies. Whether foreign funding inflows affect households, notably in more advanced economies, has received limited attention. Recent research on emerging market sector-level data by [Garber et al. \(2019\)](#) documents that *aggregate* household credit rises in response to capital inflows. Relatedly, [Saffie et al. \(2020\)](#) show that financial openness triggers a reallocation of resources towards firms with high expenditure elasticity activities. Yet, this literature has not devoted attention to whether foreign capital inflows affect the composition and allocation of credit *between* households.

This paper aims to address this gap in the literature by investigating the effects of increased foreign capital inflows on the household sector in Germany. Specifically, we focus on the period when the European Central Bank (ECB) implemented its negative interest rate policy and quantitative easing programs in 2014/2015. Net cross-border bank flows into the euro area increased significantly, rising from -3.5% of GDP in 2014:Q1 to almost +3% in 2016:Q3, providing new funds to euro area banks. In Germany, the largest euro area economy, the increase in bank inflows was even more pronounced, as we document below.

To study the effects of these inflows, we use granular household-level data combined with detailed supervisory bank balance sheet information. We find that the rise in cross-border bank inflows induced banks with greater initial dependence on non-core funding (NCF), i.e., interbank borrowing, money market funding and debt securities financing, to raise their consumer loan supply to low-income households. In economic terms lower income households

experience a 51 percentage points higher growth rate in uncollateralized consumer credit compared to higher-income households. Lower income households who have their main bank relationship with a more exposed bank, i.e., with greater dependence on non-core funding, experience an even larger growth differential of 83 percentage points. When a bank is weakly capitalized, the effects are even stronger, consistent with the literature on the risk-taking channel of monetary policy transmission (e.g., [Jiménez et al., 2014](#)). The growth in consumer credit mainly benefits households on the extensive margin, i.e., households, who did not receive uncollateralized credit before, see increases in consumer credit volumes. We find no evidence of increased risk-taking in banks’ mortgage lending.

The increase in banks’ consumer lending to riskier households is consistent with theoretical predictions. [Acharya and Naqvi \(2012\)](#) show that an increase in bank liquidity caused, for instance, by capital inflows, worsens bank agency problems and induces loan officers to increase their lending to riskier loan applicants. [Martinez-Miera and Repullo \(2017\)](#) argue that a rise in the supply of savings, as occurs through capital inflows, reduces interest rate margins and incentivizes banks to maintain profitability by cutting back on costs, particularly on monitoring and screening. This leads to increased lending to riskier borrowers. Similarly, [Rajan \(2006\)](#) highlights that lower interest rates, potentially stemming from capital inflows, can lead to risk-taking and a search for yield by banks.

We study the impact of cross-border flows on banks’ lending to households by leveraging two granular household-level data sets. The first data set, used for our benchmark analysis, is the German Panel on Household Finances (PHF), which contains detailed survey information on households’ credit, income, wealth, consumption and background characteristics. In our main analyses we exploit a peculiar feature of the German banking system: certain banks—savings and cooperative banks—are restricted to operating within specific geographical boundaries of administrative regions. These regions align with the regional information available for households. As the PHF also includes questions about households’ primary banking relationships, we can link households to a specific bank when their main

relationship is with a savings or cooperative bank. Using rich supervisory data from the Bundesbank, we quantify the relationship between bank flows and lending to households as a function of banks' exposure to cross-border flows. In the second part of our analysis, we provide external validation for our findings by employing household data from the ECB's Household Finance and Consumption survey (HFCS) for the euro area. These data enable us to confirm, within a broader sample, that bank flows disproportionately affect banks' lending to lower-income households.

We exploit the surge in euro area bank inflows in 2015-17, which was largely driven by the ECB's implementation of non-conventional monetary policy tools, to estimate difference-in-differences regressions for various measures of credit and consumption for these households and banks. Our main outcome variable of interest is the growth rate of a household's consumer or mortgage credit. We measure a bank's exposure to cross-border bank flows as its pre-2015 NCF ratio, i.e., interbank borrowing plus money market and debt securities issued as a share of total assets. This follows [Baskaya et al. \(2017\)](#), who demonstrate that banks with higher NCF ratios exhibit a lending behavior more sensitive to cross-border capital flows. Intuitively, banks that depend heavily on interbank funding and other types of non-core funds should be more affected by cross-border bank flows, while retail deposits are typically quite sticky and hence largely unrelated to such flows. To assess whether more exposed banks especially increase lending riskier households, we analyze the interaction between the banks' non-core dependence and households' riskiness, proxied by initial income ([Mayer, 2023](#), [Beer et al., 2018](#), [American Express, 2022](#)). We further identify the accompanying real effects by studying various components of a household's consumption expenditures.

Our analysis provides three main results. First, we show that more exposed banks, i.e., those more dependent on interbank funding, increase their lending to low-income households in response to the bank inflow shock. Economically, our estimates imply that a low-income household, in the 25th percentile of the income distribution, compared to a high-income household, in the 75th percentile, experiences a 51 percentage point higher growth rate

of consumer credit after the bank inflow shock. This growth rate differential rises to 83 percentage points for low-income households whose main banking relationship is with a more exposed bank, i.e., one in the 75th percentile of the NCFR distribution. In contrast, mortgage credit is largely unaffected by the inflow of foreign bank funds. These effects remain robust when accounting for a range of fixed effects and household characteristics. Additionally, we observe a weakly positive shift in consumer lending towards younger and migrant households. The growth in credit is driven by the extensive margin, i.e., by loans to households who had not previously borrowed from exposed banks before the foreign inflow shock. We further establish that the increase in lending to low-income households is most pronounced for poorly capitalized banks, which improve their profitability as a result of the credit expansion. Micro data from a group of euro area countries confirm our findings in a broader sample of households. Second, we show that lower-income households whose primary banking relationship is with a bank with greater dependence on non-core funding increase their consumption expenditures: Households in the 25th percentile of the income distribution increase their non-durable expenditures by 28.7% relative to those in the 75th percentile. Third, using confidential supervisory bank data, we provide a blueprint of the precise channel through which foreign bank inflows reach German regional banks and their household customers. We establish that German banks with a higher NCFR before the foreign bank inflow shock experience a relative rise in non-core funding volumes after the shock. Direct deposits by non-area banks at regional German banks grow approximately five times faster than indirect deposits, where foreign banks make deposits at large German banks that pass on "excess liquidity" to smaller regional banks. Non-euro area banks thus directly reach smaller German banks via the interbank market, but this mechanism is reinforced through a trickle-down effect from large German banks.

Together, these results provide new evidence that foreign bank inflows are quantitatively important for household lending in advanced economies like Germany, not only in emerging and developing markets. Foreign bank flows operate through both the international network

of large global banks (Cetorelli and Goldberg, 2012, Correa et al., 2021), as well as via regional banks dependent on non-core funding.

We address several potential threats to our analysis and identification strategy, demonstrating that our findings are highly robust. First, our exposure measure, the NCF ratio, may not be randomly distributed across banks and could correlate with bank controls, potentially biasing our estimates. We therefore include a large set of bank controls and additionally interact them with household characteristics. Our results remain quantitatively and qualitatively unchanged. Second, our findings could depend on the specific gross exposure measure we chose. To check this, we rerun our regressions using banks’ net exposure to non-core funding flows and find our results are unaffected. Third, our analysis assumes that households borrow primarily from their main relationship bank. To dispel any concern that our results could be driven by an unobserved shift to increasingly important online banks, we re-run our main regressions on a sub-sample of the most loyal bank customers. The results confirm the robustness of our findings for households with tightly defined banking relationships.

Finally, we conduct a placebo test using data from a period without any substantial change in cross-border bank flows. We find no shift in more exposed banks’ consumer lending to low-income households during that period. Similarly, we estimate our regressions with placebo outcomes, such as changes in households’ income or net worth, or use the share of tangible fixed assets over total assets as a placebo bank-level *exposure* variable. In all of these regressions, our coefficients of interest turn statistically insignificant, providing indirect evidence in support of the parallel trend assumption.

We contribute to four strands of literature. First, a strand of research shows that (emerging economy) banks have a highly procyclical access to non-core funding from global capital markets (Giovanni et al., 2021) and, when more dependent on NCF, raise their loan supply in response to foreign NCF inflows (Baskaya et al., 2017).¹ Te Kaat (2021) shows that

¹Sarmiento (2022) studies the taper tantrum episode and shows that Colombian firms experienced a worsening of credit access from banks receiving funding from abroad. Using bank-level data, Kneer and Raabe (2019) show that higher capital affects lending by UK banks.

cross-border debt flows increase credit to less profitable firms in the euro area. [Garber et al. \(2019\)](#) study credit to the aggregate household sector in Brazil. While these papers identify the effects of cross-border flows on *aggregate* bank lending or corporate lending, we complement them with unique micro evidence on how households’ access to (and composition of) credit is affected by cross-border bank flows. By studying granular household-level data we can show that particularly low-income households benefit from a rise in credit supply and that foreign-funding induced credit growth primarily translates into uncollateralized, riskier consumer credit by weaker banks.

Second, we contribute to the literature on banks as transmitters of financial and monetary shocks. [Cetorelli and Goldberg \(2012\)](#), [Baskaya et al. \(2017\)](#), [Temesvary et al. \(2018\)](#), and [Correa et al. \(2021\)](#) examine how global banks transmit shocks. [Iyer and Peydró \(2011\)](#), [Puri et al. \(2011\)](#), [Schnabl \(2012\)](#), [Ongena et al. \(2015, 2018\)](#), [De Jonghe et al. \(2020\)](#) and [Hale et al. \(2020\)](#) investigate how negative financial shocks from various crises impact banks’ lending practices through linkages across states and countries, as well as their effects on business customers. These effects depend both on the banks’ ownership, their sources of funding, liquidity and local importance. We complement this literature in two ways. We show that not only large global banks but also small regional banks, in Germany, without access to foreign branches but exposed to fluctuations in international funding flows through securities - and interbank markets, raise lending to *households* in response to a rise in banking inflows. In addition, we document how *positive* shocks are transmitted through cross-country interbank linkages.

Third, we contribute to the literature on financial crisis predictors.² [Schularick and Taylor \(2012\)](#) and [Jordà et al. \(2013\)](#) show that credit expansions are associated with deeper recessions and increased financial crisis risk. [Müller and Verner \(2024\)](#) further demonstrate that particularly credit booms in the household sectors can trigger boom-bust cycles and predict financial crises. [Jordà et al. \(2016\)](#) document that mortgage credit expansions lead

²See [Sufi and Taylor \(2022\)](#) for an extensive literature survey on this relationship.

to elevated financial fragility, while [Mian et al. \(2017\)](#) establish that faster household debt growth presages lower future GDP growth, especially when countries rely heavily on external debt. [Caballero \(2016\)](#) adds that capital inflow bonanzas increase the probability of banking crises. We contribute to this literature by detailing the mechanism through which bank inflows affect household borrowing. Specifically, we show that funding inflows can induce more exposed banks to raise their lending to lower-income, riskier households via uncollateralized credit, thereby exacerbating the vulnerability of poorly capitalized banks.

Finally, we complement the literature that employs credit register data to estimate the impact of different macroeconomic shocks on banks' credit allocation. [Altavilla et al. \(2020\)](#) finds that expansionary monetary policy increases banks' credit supply to the household sector, particularly when banks are poorly capitalized. [Gyöngyösi et al. \(2024\)](#) study the effects of a capital account liberalization period in Hungary and find that foreign currency mortgages reinforce the risk-taking channel of monetary policy because weakly capitalized banks lend more in foreign currency to riskier borrowers. [Epure et al. \(2024\)](#) show that macroprudential policies dampen the impact of global financial conditions on local bank credit cycles. We enhance this literature by detailing how credit shifts across heterogeneous households and how this translates into consumption responses.

This paper proceeds as follows. Section [2](#) presents the data. In Section [3](#), we report the aggregate dynamics of cross-border bank flows. Section [4](#) discusses our identification strategy. Section [5](#) presents our main results using German household-bank-level data. To show external validity, we also provide complementary results with household-level data for several euro area countries. Section [6](#) studies the mechanisms through which cross-border bank inflows affect banks' household lending. In Section [7](#), we gauge the extent to which credit growth spills over to household consumption. Section [8](#) concludes.

2 Data

This paper leverages two unique data sets to investigate the relationship between capital flows, household lending, and consumption. First, we analyze household-bank-level data from Germany to establish a robust causal link. Second, we employ household-level data from a selection of euro area countries to demonstrate the external validity of our findings. In the following two subsections, we provide a comprehensive description of each data set.

2.1 Household-Bank-Level Data for Germany

For our benchmark analysis, we rely on household-level data from the Deutsche Bundesbank’s Panel on Household Finances (PHF).³ This data set contains information on households’ characteristics, wealth, indebtedness, and income across three waves (2010-2011, 2014, and 2017), with between 3,500 and 5,000 households in each wave. In cases where households do not respond to specific questions, the Bundesbank uses imputation methods, utilizing households’ responses to other survey questions. The PHF is an integral part of the euro area’s (EA) Household Finance and Consumption Survey (HFCS) that collects ex ante harmonized micro data on households in every EA country.

We follow the approach of [Kindermann et al. \(2021\)](#) and use the first of the five available PHF implicates for our analysis because only a few variables in the data set suffer from missing observations. We calculate our primary outcome variable, household-level nominal credit growth, as the change in the logarithm of either consumer loans or mortgages.^{4 5} To proxy for a household’s riskiness, we follow [Mayer \(2023\)](#) and use the logarithm of household income.⁶ Other household characteristics we control for are the log of net worth, a dummy

³We use the following PHF versions: <https://DOI10.12757/Bbk.PHF.01.04.01> (Wave 1), <https://DOI10.12757/Bbk.PHF.02.04.01> (Wave 2), and <https://DOI10.12757/Bbk.PHF.03.02.01> (Wave 3).

⁴To prevent exclusion of households with zero credit volumes, we add one to all self-reported credit volumes.

⁵Given low German inflation rates during 2010-17 we obtain, in line with expectations, similar results when we use real credit growth as outcome variable. The attendant results are available upon request.

⁶[Beer et al. \(2018\)](#) and [American Express \(2022\)](#) also provide evidence that income is negatively correlated with default risk. [Campbell and Cocco \(2015\)](#) explain that lower income households are more likely to default

for households renting their main residence, the household head’s age, a dummy for foreign citizenship and a dummy indicator for households expecting a rise in real income over the next twelve months. In some specifications, we also utilize information on households’ self-employment income, as well as unemployment benefits or other regular social transfers.

In the final part of our analysis, we study the household-level consumption effects of improved credit access. We compute several consumption variables, including the logarithm of durable and non-durable consumption.⁷ The PHF does not contain direct information on durable consumption. Following [Le Blanc and Schmidt \(2018\)](#), we compute total household consumption as the difference between income and net saving, where net saving is defined as the change in financial assets after accounting for changes in outstanding debt. To obtain a household’s durable consumption, we then subtract non-durable consumption from total consumption. The PHF provides information about two distinct sub-components of non-durable expenditures, food and drinks at home and expenses on food and drinks outside the home (“restaurant”).

The PHF data allow us to identify the link between households and their main bank because it contains information on whether the household’s primary bank is a savings bank, a cooperative bank, a commercial bank, a Landesbank, or any other type of bank. Savings and cooperative banks in Germany are only permitted to operate within the geographical boundaries of particular administrative districts, so-called “Landkreise” that correspond to US counties. We can therefore connect 67% of households in our sample who have their primary relationship with a savings or a cooperative bank to their main bank using regional identifiers.⁸

on their (ARM) mortgage loans because a default has a bigger cash-flow relief effect.

⁷To maximize the number of observations and not to lose zero-valued consumption values, we add a one to all consumption values before taking the log.

⁸We determine the area of operation of a savings or cooperative bank based on the location of its headquarters. Some banks operate in multiple regions. Because we do not have data on banks’ market shares in the various regions, we assign each banks to the region where it is headquartered. The alternative, i.e., matching banks to all regions where they have non-zero operations would lead to a strong over-representation of the larger regional banks. These typically focus their activities on their headquarter region while providing a small number of loans to firms and households in neighboring regions. In such cases where multiple banks operate in a specific administrative region and an exact match between a household and its bank is

This direct link enables us to estimate the effect of bank flows on household lending as a function of a bank’s exposure to cross-border flows. Specifically, we use data from the Bundesbank’s monthly balance sheet statistics (BISTA) and income statement statistics (GuV) to compute a bank’s exposure to cross-border bank flows as the sum of its 2014 interbank deposits plus money market and debt securities issued as a proportion of total assets.⁹ The intuition behind this choice is that banks with a greater non-core dependence are likely to benefit more from bank inflows that increase the availability of interbank funding. In contrast, as retail deposits are relatively sticky and hence largely unrelated to such flows, banks dependent on retail deposits will be less affected by a surge in bank flows. For robustness, we compute banks’ 2014 exposure to cross-border bank flows both in terms of net and gross interbank deposits as a share of total assets, while abstracting from money market and debt securities components. We further focus on the interbank transmission channel and break down gross interbank deposits into their domestic, euro area, and non-euro area components. Regressions include several bank controls from BISTA: size (log of total assets), return on assets or equity, the liquidity ratio (cash, central bank reserves, and treasuries held over total assets), and the leverage ratio (total capital over total assets), all at their 2014 values.

Finally, we make two assumptions about the link between households and banks. First, because data on a household’s main bank (type) is only available in the first and second wave, we assume that households do not switch main bank between waves two and three. Second, we assume that a household takes out any new loan at its main bank and not at another bank. This is consistent with Germany’s tradition of strong relationships between households and banks. For instance, [Puri et al. \(2017\)](#) find that households typically apply for a loan at the bank where they have their bank account, with more than 80% of loan

not possible (which is the case for 37% of the savings banks and 75% of the cooperative banks across all 401 German regions), we use weighted average bank ratios for such households, with banks’ total assets serving as weights. Our results are robust to excluding observations without an exact identification of the bank-household relationship.

⁹See [Schaefer and Stahl \(2023\)](#) and [Stahl and Scheller \(2023\)](#) for data details.

applicants having been customers for five years or more. Long-standing bank–depositor relationships also facilitate access to uncollateralized credit, including consumer loans. In Section 5, we provide further evidence in support of these assumptions.

Table 1 reports summary statistics for the German household-bank data set. Both consumer and mortgage credit were contracting during our sample period. Of the households in our sample, 31% rent their main residence and 6% have foreign citizenship. The average household age is 59.7 years. In our sample, 29% of households have at least one member receiving unemployment benefits or other regular social transfers excluding pensions, and 18% receive income from self-employment. Banks have an average NCFR of 13.5%, a return on assets of 0.15%, a capital ratio of 5.7% and a liquidity ratio of 1.4%. Table A2 shows that most of these characteristics are similar for households whose main relationship is with both more and less exposed banks, with the exception of the main dependent variables. Specifically, more exposed banks have lower consumer credit growth over the sample period.

2.2 Household-Level Data for the Euro Area

We incorporate a second data set sourced from the European Central Bank’s Household Finance and Consumption Survey (HFCS), encompassing comprehensive household-level data from 22 European countries. The data set spans three distinct periods: 2009-2011, 2013-2014, and 2016-2018. However, not all countries in the data set conduct their national surveys as a panel. Since our identification strategy relies on the comparison of households’ credit volumes before and after cross-border bank inflow shocks, we exclude countries that lack repeated household data across waves. Consequently, our final regression sample comprises almost 18,000 households from seven countries: Belgium, Cyprus, Finland, France, Germany, Italy, and Spain. To maintain consistency, we utilize the same data imputation method as for the German data set.

Because the PHF is a subset of the euro area-wide HFCS, the questions in both panels are nearly identical. Consequently, we can calculate the same variables outlined in Section

Table 1 SUMMARY STATISTICS FOR GERMAN HOUSEHOLDS / BANKS

Variable	Observations	Mean	SD	5th	95th
Δ Mortgages	1,536	-15.08	415.86	-1012.67	999.88
Δ Consumerloans	1,536	-31.12	396.71	-851.74	829.43
Consumption(non-durable)	1,536	9.26	0.73	8.19	10.31
Consumption(durable)	1,468	9.79	1.19	8.19	11.09
Consumption(food)	1,536	8.53	0.56	7.62	9.39
Consumption(restaurant)	1,536	6.46	2.12	0.00	8.34
Ln(Noncore)	14,615	11.26	2.10	8.01	14.61
Ln(Interbank)	14,615	11.18	2.04	8.00	14.51
ROA	13,524	0.04	2.48	0.00	0.42
ROE	13,524	1.89	16.99	0.00	6.64
Net wealth	1,536	12.05	1.87	8.22	14.31
Income	1,536	10.85	0.75	9.61	11.95
Renter	1,536	0.31	0.46	0.00	1.00
Age	1,536	59.71	14.30	32.00	80.00
Foreign	1,536	0.06	0.24	0.00	1.00
Income Exp.	1,536	0.08	0.27	0.00	1.00
Unemployed	1,536	0.29	0.45	0.00	1.00
Self-Employed	1,536	0.18	0.38	0.00	1.00
Non-Core	1,536	13.47	5.84	5.13	23.77
Gross Interbank	1,536	12.54	5.65	4.54	21.65
Gross Domestic Interbank	1,536	0.02	0.98	-1.41	1.63
Gross EA Interbank	1,536	0.02	1.02	-0.38	1.98
Gross Non-EA Interbank	1,536	-0.02	0.36	-0.08	0.10
Net Interbank	1,536	4.93	7.72	-8.42	16.86
Size	1,536	14.46	1.17	12.64	16.22
ROA	1,534	0.15	0.08	0.02	0.28
Equity	1,536	5.67	1.02	4.02	7.55
Liquidity	1,536	1.40	0.43	0.85	2.32

NOTE. The table reports summary statistics for the German bank-household data set. The first block of variables are the outcome variables in the different stages of the analysis at either the household or bank level. The second one contains the household-level controls and the third block contains the bank controls, both of which are fixed in the year 2014. Household-level data come from the PHF and span three periods: 2010-2011, 2014, and 2017. We provide data definitions and sources in Table A1.

2.1 using these data with two exceptions. First, Finland and France provide data for only two of the survey waves. We therefore use the log of credit volumes instead of log-differences as the outcome variables to avoid reducing our sample size. Second, the HFCS contains income expectations only in the third survey wave, which prevents us from incorporating this variable into our difference-in-differences regressions.

To account for the varying intensity of cross-border bank flows across countries in the euro area, we match the European household data with aggregate cross-border bank flow data

obtained from the BIS Locational Banking Statistics (BIS-LBS). This measure is computed as the FX - and break-adjusted change in a country’s banking sector liabilities vis-a-vis banks in all other countries, net of the corresponding change in the banking sector’s foreign assets, as a fraction of nominal GDP.¹⁰

Table 2 presents the summary statistics for the European sample. The two credit variables (in logs) have mean values of 2.3 and 3.3, with mortgages showing greater standard deviation than consumer loans. Heterogeneity across households is more pronounced in net wealth than in income. The average age of household heads in the sample is 57 years, approximately 10% of households hold foreign citizenship, and one fifth are renters. Finally, the ratio of net bank inflows over GDP has an average value of 0.6%, ranging from -1.4 to 7.0% between the 5th and 95th percentile. Table A3 further provides separate summary statistics for more- and less-exposed countries.

Table 2 SUMMARY STATISTICS FOR EUROPEAN HOUSEHOLDS

Variable	Observations	Mean	SD	5th	95th
Ln(ConsLoans)	34,980	2.3	4.0	0.0	10.1
Ln(Mortgages)	34,980	3.3	5.1	0.0	12.2
Net wealth	34,980	12.1	1.9	8.3	14.6
Income	34,980	10.6	0.9	9.2	12.0
Renter	34,980	0.2	0.4	0	1
Age	34,980	57.1	15.3	31	81
Foreign	28,270	0.1	0.3	0	1
Bank flows	34,980	0.6	2.9	-1.4	7.0

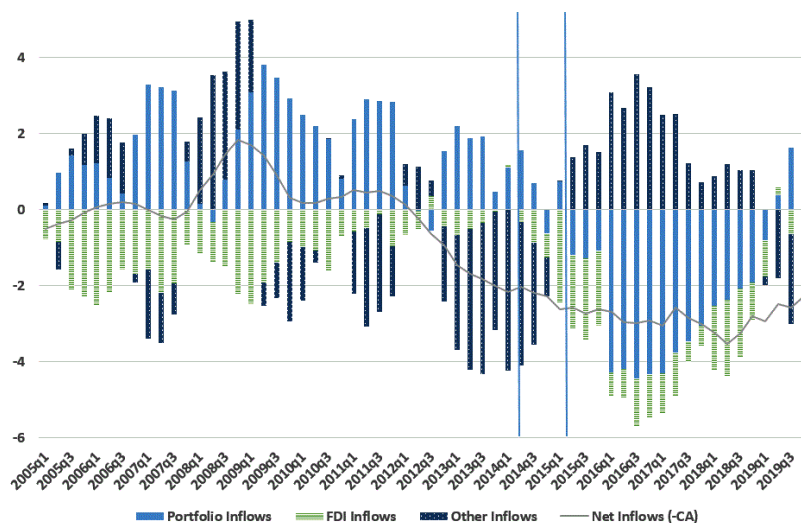
NOTE. The table reports summary statistics for the sample from the European Central Bank’s Household Finance and Consumption Survey (HFCS). This contains household-level data from 22 European countries. The data set spans three periods: 2009-2011, 2013-2014, and 2016-2018. We exclude data from countries that do not conduct the surveys as a panel. Our final regression sample comprises data from Belgium, Cyprus, Germany, Finland, France, Italy and Spain. The summary statistics are reported for all households that are included in Table 7, column (1). We provide data definitions and sources in Section 2.2.

¹⁰Break-adjusted means that the BIS corrects cross-border flows for breaks in the reporting population and/or reporting methodology.

3 Cross-Border Bank Flow Dynamics

Figure 1 illustrates the dynamics of euro area net cross-border capital flows, measured as the negative of the current account, and disaggregated into net FDI, net portfolio investment, and net other investment inflows. The latter category primarily consists of cross-border interbank credit. The figure shows that overall capital flows were persistently negative between 2011 and 2019. However, after the ECB's implementation of a negative interest rate policy in 2014:Q2 and its QE program in 2015:Q1, portfolio inflows as a percentage of GDP declined and turned negative, while other investment inflows, including interbank inflows, increased substantially. These dynamics reflect that, as foreign investors sold euro-denominated government bonds to accommodate the ECB's asset purchase program (Bergant et al., 2020), the revenues from those asset sales provided new funds to euro area banks.

Figure 1 THE EURO AREA FINANCIAL ACCOUNT



NOTE. This figure shows the euro area financial account, with the solid line depicting total net capital inflows (the negative of the current account), and the bars representing portfolio investment, FDI, and other investment inflows, respectively, all in net terms and as a percentage of euro area GDP. The flow variables are smoothed by using four-quarter moving averages before dividing by GDP. The vertical lines mark the implementation of negative rates in 2014:Q2 and of the ECB's QE program in 2015:Q1. Sources: BIS, ECB and FRED. See Data Appendix for details.

Figure 2, Panel A, shows that breaking down the financial account using BIS-LBS data and focusing on net cross-border bank inflows produces a similar pattern of higher inflows

to banks located in the euro area. When we split net bank inflows into gross inflows and outflows, Panel B indicates that a change in gross inflows was driving the increase in net flows, i.e., banks located outside of the euro area expanded their interbank lending to banks within the euro area. Panel C demonstrates that countries in the core of the euro area were the recipients of the growing inflows in 2015-17. This suggests that foreign investors mainly provided cross-border funds to banks in the northern euro area, which were perceived as safer at the time. In Germany, bank inflows increased significantly, rising from -6% in 2013 to +4% in 2016 (Panel D). In our main regression specifications, we leverage this sharp increase in German bank inflows in a difference-in-differences setting that exploits the varying intensity with which these flows affect different banks. For external validation, we use euro area data to leverage cross-country variation in bank inflows as documented in Panel C.

4 Empirical Specification

4.1 German Benchmark Specification

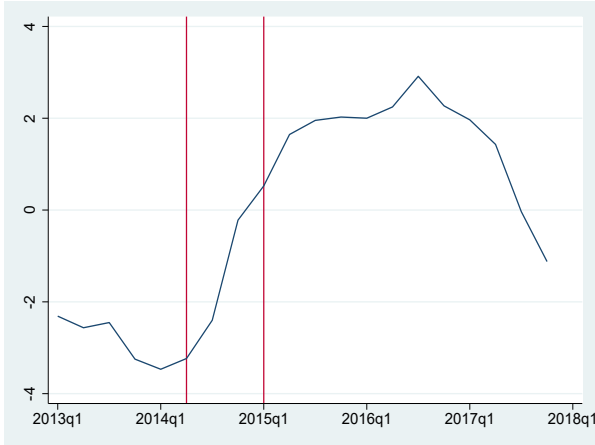
In our benchmark specification, we use German survey data to identify the effect of cross-border bank flows on banks' lending to households. This is achieved by estimating a difference-in-differences model that exploits the increase in cross-border bank flows into Germany after the ECB's implementation of its negative interest rate policy and QE programs in 2014/15. Our regressions are specified as follows:

$$\Delta Y_{h,b,t} = \alpha_t + \alpha_h + \beta \cdot (\text{Post}_t \times X_{h,2014}) + \epsilon_{h,b,t}, \quad (1)$$

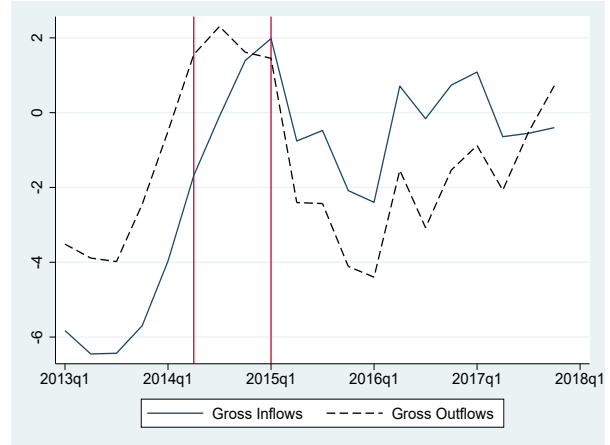
where Y represents the logarithm of either total mortgage or total consumer loans of household h borrowing from bank b . The key variable of interest is the interaction between the Post-dummy, which equals one for the survey wave following the recovery of bank flows (wave 3) and zero otherwise, and various pre-inflow household characteristics. These controls in-

Figure 2 BANK FLOWS IN THE EURO AREA

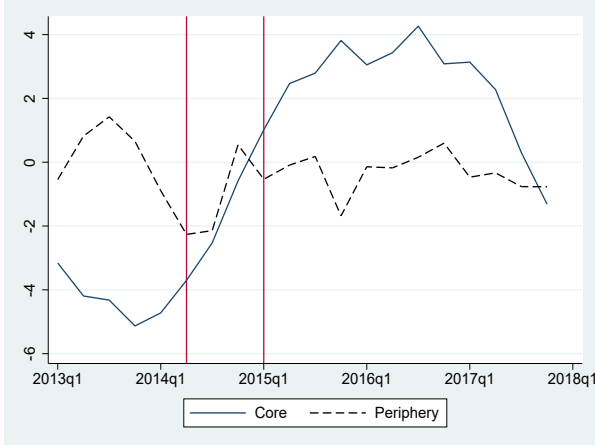
Panel A: Net Bank Inflows - Entire Euro Area



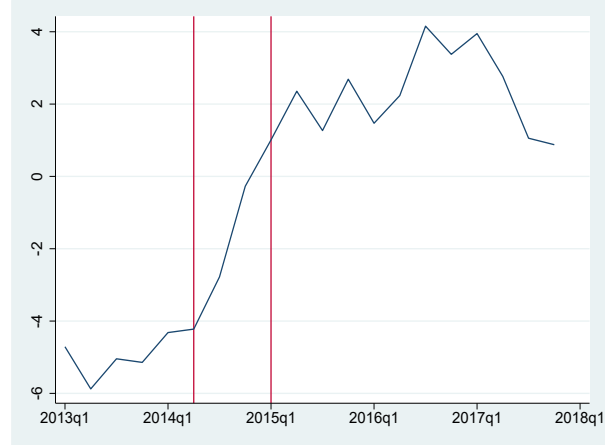
Panel B: Gross Bank Flows - Entire Euro Area



Panel C: Bank Inflows - Core vs Periphery



Panel D: Bank Inflows - Germany



NOTE. This figure depicts the dynamics of net cross-border bank inflows in the euro area (Panel A), its breakdown into gross inflows and outflows (Panel B), net inflows separately for countries in the periphery (Cyprus, Greece, Ireland, Italy, Portugal, Spain) vs core (all other countries) of the euro area (Panel C), and for Germany only (Panel D). Bank flows are scaled by nominal GDP and then smoothed by computing four-quarter moving averages. The vertical lines mark the implementation of negative rates in 2014:Q2 and of the ECB's QE program in 2015:Q1. Sources: Fred and BIS-LBS

clude the logarithm of household income, as we are particularly interested in whether bank inflows induce an increased credit allocation towards low-income, riskier households. Additional household characteristics are included as controls, interacted with the Post-dummy, to capture their potential effects on lending. Equation (1) also contains household and time fixed effects, denoted by α_h and α_t , to control for unobserved household-specific, time-invariant characteristics and aggregate conditions that equally impact all households. The standard errors here and in the following specification are heteroskedasticity-robust, but clustering them at the country level leads to consistent results (not reported).

In a second step, our benchmark specification, we expand the regression by incorporating a triple interaction term involving the interaction between the Post-dummy, the various household characteristics, fixed at their pre-treatment levels, and a bank’s initial NCFR. The expanded equation takes the following form:

$$\begin{aligned} \Delta Y_{h,b,t} = & \alpha_t + \alpha_h + \gamma \cdot (\text{Post}_t \times \text{Non-core}_{b,2014}) + \sigma \cdot (\text{Post}_t \times X_{h,2014}) + \\ & \nu \cdot (\text{Non-core}_{b,2014} \times X_{h,2014}) + \omega \cdot (\text{Post}_t \times X_{h,2014} \times \text{Non-core}_{b,2014}) + \epsilon_{h,b,t}. \end{aligned} \quad (2)$$

This will be our preferred specification because it enables us to explore whether cross-border bank flows induce *more exposed* banks to exhibit a heightened risk appetite in their lending practices towards households, where exposure is measured by banks’ NCFR. This follows [Baskaya et al. \(2017\)](#), who show for Turkey that banks with greater NCFRs are more affected by cross-border flows than those reliant on customer deposits. We therefore hypothesize that the coefficient ω will be negative, i.e., banks which are expected to benefit more from the upswing in cross-border bank flows will increase their lending to lower-income (risky) households relative to other banks.

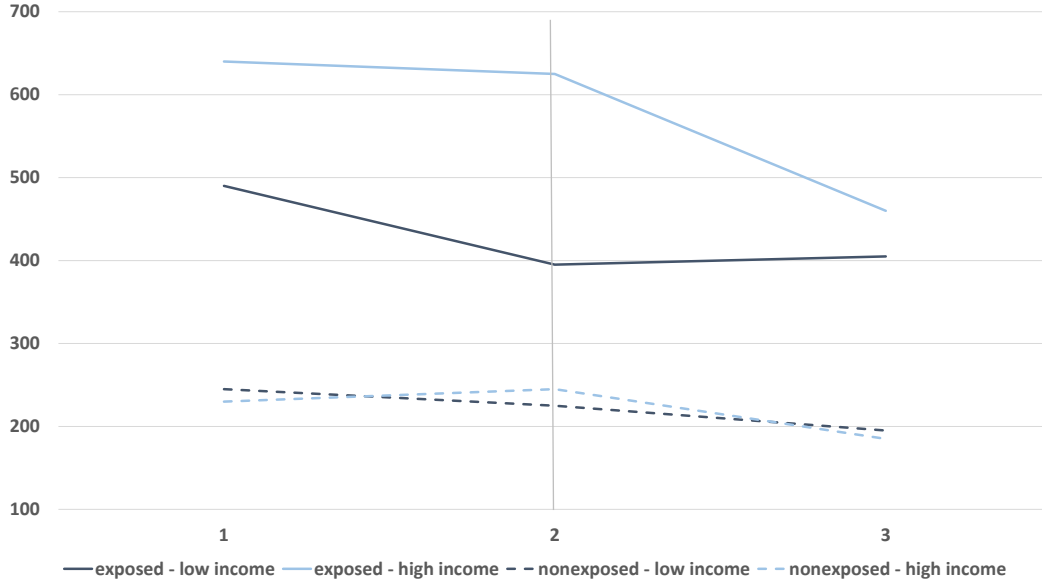
In our most saturated model specification, we include not only household and time fixed effects, but also bankgroup-location-income-time fixed effects. Here, “bankgroup” refers to whether a household’s main relationship bank is a savings or cooperative bank, “location”

represents one of the 401 administrative German regions, “time” corresponds to the survey wave, and “income” denotes the decile of the household income distribution. These fixed effects align with [Degryse et al. \(2019\)](#), who show that industry-location-size-time fixed effects control for loan demand in bank-firm relationships in a similar manner to Khwaja-Mian’s firm-time fixed effects ([Khwaja and Mian, 2008](#)). Similarly, our bankgroup-location-income-time fixed effects intend to absorb any heterogeneity that is specific to a cluster of households in a certain region, with a certain bank group preference, of a specific income, at a particular point in time. By controlling for the bulk of households’ changes in loan demand, our estimation will identify shifts in credit supply following cross-border bank inflows.

The central assumption underlying the difference-in-differences regressions is that, in the absence of cross-border bank flows, banks with a higher non-core dependence would have exhibited the same trend in lending behavior as banks with a lower dependence. To validate this assumption, as a first step, [Figure 3](#) shows the time series dynamics of the logarithm of consumer credit—the outcome variable we find most affected by cross-border bank flows—for four distinct bank-household combinations: more (less) exposed banks and low (high) income households. As becomes clear from [Figure 3](#), prior to the increase in bank inflows starting in 2015, more exposed banks, i.e., those with a NCFR in the upper 67% of the distribution, and less exposed banks (below the 33rd percentile) followed the same trends in lending to low-income households. After the increase in bank inflows, more exposed banks increase their consumer lending to these households, while less exposed banks did not. For high-income households, we see similar consumer credit dynamics independent of bank inflows and bank exposure. In [Section 5.3](#), we will also estimate a proper placebo regression on a sample period without a surge in bank flows. When doing so, our benchmark results disappear, providing further evidence in support of the parallel trend assumption.

For the difference-in-differences estimates to be unbiased, the treatment status should be assigned randomly. When this condition is not satisfied, for example because banks’ non-core ratios are correlated with other bank covariates, properly controlling for these covariates will

Figure 3 PARALLEL TRENDS BEFORE THE BANK INFLOW SHOCK



NOTE. This figure shows the aggregate log of consumer credit volumes in our German final PHF sample for four distinct bank-household combinations: (i) low-income households (lowest 50%) and exposed banks (top 67% of non-core ratios); (ii) low-income households and less exposed banks (lowest 33%); (iii) high-income households (upper 50%) and exposed banks; (iv) high-income households and less exposed banks. The vertical line depicts the start of cross-border bank flows into Germany. Sources: PHF, Bundesbank Supervisory Data.

satisfy the conditional mean zero assumption and ensure unbiased estimates ([Roberts and Whited, 2013](#)). Therefore, we include a broad set bank covariates fixed at their pre-inflow wave 2 level interacted with the Post-dummy and the household characteristics in matrix X. We show later on that the inclusion of these interactions has a negligible impact on our baseline estimates, suggesting that non-random treatment allocation does not jeopardise our identification.

4.2 External Validity: Euro Area Data

To establish external validity of our results, we also use data for nearly 18,000 households from seven euro area countries: Belgium, Cyprus, Finland, France, Germany, Italy, and Spain. As described in Section 2, the European data do not allow for a linkage between households and individual banks. This limitation prevents us from conditioning the link

between cross-border bank flows and household credit on banks' exposure to such flows, which weakens identification in this part of the analysis.

Instead, these specifications use cross-country variation in the intensity of bank inflows. Specifically, we estimate the following regression:

$$\begin{aligned} \text{Log}(Y_{h,c,t}) = & \alpha_t + \alpha_h + \zeta \cdot (\text{Post}_t \times \text{Bank Inflows}_{c,2016/17}) + \kappa \cdot (\text{Post}_t \times X_{h,2014}) + \\ & \tau \cdot (\text{Post}_t \times X_{h,2014} \times \text{Bank Inflows}_{c,2016/17}) + \epsilon_{h,c,t}, \end{aligned} \quad (3)$$

where $\text{Log}(Y)$ is the logarithm of mortgage or consumer credit. In the euro area regressions, we define the outcome variables in log-levels instead of first differences, as in the benchmark regressions. The latter approach requires data from at least three survey waves and lead to the exclusion of 6,000 observations from Finland and France. The matrix X , which contains control variables, includes all variables of the German benchmark regressions, except for income expectations, which is missing in waves one and two of the HFCS survey. The Post-dummy equals one for survey wave three and zero otherwise.

Because we cannot lean on historical bank-level exposures to capital inflows, a key difference in the euro area regressions is that changes in credit now depend on a *country's* net cross-border bank inflows as a share of GDP during 2016-17. Consequently, the results from these regressions should be treated as complementary rather than causal evidence. At the country-household level, we expect that larger bank inflows will also be associated with a stronger shift in credit towards riskier households. The regressions include household and wave fixed effects to control for heterogeneity across households and over time. Some specifications add country-wave fixed effects to better absorb loan demand shifts following cross-border bank flows. Standard errors are clustered at the country-wave-level.

Importantly, the cross-country, cross-household regressions help establish that our benchmark results for Germany are not solely driven by the adoption of negative rates or QE. Instead, the results highlight the role of relative changes in cross-border bank flows. Both

monetary policy instruments were set equally across all euro area countries. The cross-country regressions enable us to disentangle bank inflow effects from monetary policy and investigate to what extent only countries encountering bank inflows experienced changes in the allocation of household-level credit, as we expect from the bank-household results for German households.

5 Empirical Findings: Credit Allocation

5.1 Benchmark Results for German Households

Here, we present our benchmark results corresponding to Equations 1 and 2. In Table 3, columns (1)-(2), we present the results for mortgage and consumer loans in specifications that interact the Post-dummy solely with household income, for now disregarding banks' differential exposures to cross-border bank flows. After the bank inflow shock, low-income households experience an increase in consumer credit, while their mortgage credit volumes remain unaffected. In columns (3)-(4), we account for bank heterogeneity by interacting the Post-dummy not only with household income, but also with the main bank's pre-shock NCFR. Consistent with our expectations, the double interaction between bank exposure and the Post-dummy is positive and statistically significant at the 1% level. Conversely, the triple interaction term has a negative and statistically significant coefficient at the 1% level, indicating that more exposed banks increase consumer lending disproportionately to low-income households. In this triple interaction model, the coefficients on the post-income double interaction are not directly comparable to those of the double interaction model of columns (1)-(2). When combining the direct treatment effect with the income interaction term, we find that the marginal treatment effect on consumer credit supply becomes negative for annual income levels above 66,000 euros, slightly exceeding the sample mean. Once again, we find no significant effect for mortgage lending.

In columns (5)-(6), we run a horse race between the household income triple interaction

term and the corresponding triple interactions with other household characteristics, whose coefficients are not shown in Table 3 due to space constraints. Our income triple interaction estimate remains significant and the coefficient estimate even increases somewhat. Without affecting the allocation along the income dimension, credit allocation displays heterogeneity along a few other household characteristics following the rise in foreign bank inflows: Younger households and those with lower income expectations receive more (consumer) credit. This means that not only households with lower past income but also those with lower expectations for future income receive more credit, pointing to a reallocation of credit towards young households and those with structurally lower incomes. Combining the estimates of columns (2) and (6), our results imply that a low-income household in the 25th percentile of the income distribution, compared to one in the 75th percentile, experiences an average 51 pp higher consumer credit growth rate after the bank inflow shock. This growth rate increases to 83 pp when the low-income household’s main relationship is with a more exposed bank, defined as one in the 75th percentile of the non-core funding distribution.

In the most saturated specification, we add location-bankgroup-income-time fixed effects to better absorb changes in households’ loan demand, as we described in Section 4. The data demands of this specification lead to a substantial reduction in the number of observations. Although the uncertainty of our estimates increases somewhat as a result, columns (7)-(8) show that our main results are qualitatively unaffected. The coefficient on the triple interaction term increases; however, its interpretation becomes less precise due to the focus on a different sample, primarily comprising larger (urban) regions.

In additional unreported regressions, we also used the log-difference in *total* outstanding household credit as the outcome variable, summing up mortgages and consumer loans. In this case, the triple income interaction coefficient is also negative and significant when location-bankgroup-income-time fixed effects are applied. The rise in consumer credit thus quantitatively dominates the dynamics of mortgage credit.

Table 3 THE EFFECT OF CROSS-BORDER BANK FLOWS ON CREDIT ALLOCATION: BENCHMARK RESULTS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Δ Mortgages	Δ ConsLoans	Δ Mortgages	Δ ConsLoans	Δ Mortgages	Δ ConsLoans	Δ Mortgages	Δ ConsLoans
Post \times Non-Core			-34.64 (68.83)	138.4*** (48.59)	-23.40 (89.88)	208.4*** (61.81)		
Post \times Income	-19.95 (21.81)	-40.75** (19.74)	-85.02 (97.65)	93.00 (62.62)	-98.48 (123.1)	153.2* (83.48)	-90.63 (1,130)	1,565* (931.8)
Post \times Income \times Non-Core			3.735 (6.467)	-12.60*** (4.514)	2.520 (8.271)	-18.78*** (5.875)	-4.634 (83.68)	-138.4* (71.24)
Other Household Controls Interacted	No	No	No	No	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Bankgroup-location-income-time FE	No	No	No	No	No	No	Yes	Yes
Obs	3,056	3,056	1,536	1,536	1,536	1,536	528	528
R^2	0.366	0.290	0.372	0.286	0.385	0.297	0.711	0.690

NOTE. Regressions are based on the PHF data. Bank exposure variables are from BISTA and GuV. Dependent variables are household-level changes in the logarithm of mortgage or consumer credit. Main regressors are interactions between a Post-dummy equalling to one for the third wave of the PHF survey and zero otherwise, and the following household-level variables fixed at their wave 2 value: log(income), log(net wealth), a dummy indicating if a household rents its main residence, age of the household head, a dummy for foreign citizenship, and income expectations. Columns (3)-(8) also include triple interactions between the Post-dummy, the aforementioned household characteristics and bank-level NCFRs from survey wave 2, where for reasons of space only the coefficients corresponding to the income triple interaction coefficient and its components are shown. Data details can be found in Table A1. Regressions include time and household fixed effects; columns (7)-(8) add bankgroup-location-income-time fixed effects. Heteroscedasticity-robust standard errors in parentheses. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Overall, these results show that low-income households benefit most from a funding shock caused by cross-border bank inflows, particularly when their primary banking relationship is with a bank that is more dependent on non-core funding. The observed rise in lending is completely driven by a change in consumer credit, not by mortgages. Consequently, we focus on consumer loans as the main outcome variable of interest for the remainder of this paper. Results for mortgage credit are available upon request. Our findings deepen our understanding of earlier work showing that banks increase risk-taking in response to significant cross-border capital inflows. We contribute to this literature by establishing that a similar mechanism exists for consumer credit at the bank-household-level, complementing earlier work at the bank- and bank-firm-level. As we show in Appendix B, the documented credit reallocation towards lower-income households also correlates with a higher profitability of more exposed regional banks.

5.2 Robustness Checks

Direct or Indirect Transmission

We next present the results of several robustness checks. First, we investigate whether access to securities markets is crucial for transmitting shocks from capital inflows. Much of the earlier research on cross-border bank flows has, for reasons of data availability, focused on global or at least large international banks. We want to understand if the effects we identify crucially hinge on smaller regional banks having similar access to securities markets, or whether these regional banks interact directly with large international financial institutions in the interbank market. To address this, we generate two alternative measures of banks' exposure to cross-border flows: the gross *interbank* dependency ratio, defined as total interbank borrowing over total assets, and the net interbank dependency ratio. Table 4, column (1), shows that our benchmark results are highly robust to excluding money market and debt securities funding from non-core funding. When capital inflows rise, as observed during the 2015-2017 period, foreign capital reaches banks not only through securities markets but also directly

through interbank markets. Column (2) indicates that the strength of the transmission of foreign shocks also depends on banks' net exposure to cross-border interbank funding.

Rural vs Urban Areas

Our analysis leverages the unique regional role of savings and cooperative banks. Although suitable regional credit data for Germany are unavailable, the local market shares of savings and cooperative banks are typically larger in rural areas. Conversely, larger commercial banks maintain a stronger office presence in urban areas, likely implying a smaller market share for regional banks in these regions. If switching behavior matters and large banks respond differently to capital inflows than regional banks, we expect our findings to weaken in urban areas. To test this, columns (3) and (4) split the sample into banks located in urban areas (Stadtkreise) and rural areas (Landkreise). Consistent with our expectations, the benchmark results are highly robust in rural areas. In urban areas, however, the results are less conclusive: while the triple interaction estimate remains negative and quantitatively similar to that in rural areas, it is not statistically significant. This is likely due to the substantially smaller sample size in this specification, reflecting that households in urban areas are more often served by large commercial banks excluded from our data set. Thus, the transmission in urban areas may well resemble that in rural areas, but our empirical setting does not allow for its identification.

Stricter Identification of Bank Relationship

Regions in our sample have an average of 1.2 savings banks, reflecting that the vast majority of regions have only one savings bank. In most cases, our matching procedure therefore exactly identifies the link between households and savings banks. However, regions have an average of 3.4 *cooperative* banks, making the bank-household pairing less precise for clients of cooperative banks.

Table 4 ROBUSTNESS: BANK EXPOSURE, RURAL VS URBAN, BANK PRESENCE

	(1) Gross Expos	(2) Net Expos	(3) Urban	(4) Rural	(5) Sav. Banks	(6) Single Bank	(7) Low Pres	(8) High Pres	(9) IHS Credit
Post \times Income	105.2 (79.99)	-46.65 (39.74)	101.7 (130.8)	98.68 (108.0)	9.54 (81.64)	-10.20 (94.85)	-19.02 (102.9)	132.4 (83.94)	168.1* (90.47)
Post \times Bank Exp.	197.4*** (64.02)	107.0** (46.22)	190.8 (118.2)	132.5* (78.45)	104.2* (60.16)	124.7 (80.32)	-20.08 (85.21)	179.9*** (64.74)	227.0*** (67.08)
Post \times Income \times Bank Exp.	-16.23*** (6.071)	-9.731** (4.549)	-15.08 (10.32)	-14.82** (7.276)	-9.41* (5.62)	-11.23 (7.62)	2.63 (8.16)	-16.85*** (6.02)	-20.49*** (6.361)
Household FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	1,536	1,536	458	1,062	856	550	600	828	1,536
R^2	0.454	0.545	0.333	0.295	0.285	0.272	0.251	0.303	0.295

NOTE. The dependent variable is the household-level change in the logarithm of consumer credit (columns 1-8) or the change in IHS transformed consumer credit (column 9). IHS is the inverse hyperbolic sine ("arcsinh") transformation as in [Bellemare and Wichman \(2020\)](#). Our regressions are based on the PHF data. Bank exposure variables originate from BISTA and GuV. The main regressors are the triple interactions between a Post-dummy equal to one for the third wave of the PHF survey and zero otherwise, bank-level exposure to cross-border flows measured in wave 2, and the following household-level characteristics fixed at the wave 2 value: log of income, log of net wealth, a dummy measuring whether a household rents the main residence, age of the household head, a dummy measuring whether a household has a migrant background, and income expectations. The bank exposure variable is the NCFR in columns (3)-(9), and the gross and net interbank liabilities, respectively, in columns (1)-(2). Most interaction estimates are not displayed to conserve space. In columns (3) and (4), we split the sample into urban and rural regions. In column (5), we only consider households borrowing from savings banks and in column (6), we additionally drop regions where multiple savings banks operate. Column (7) and (8) focus on regions with below-median and above-median regional bank presence. Data details can be found in [Table A1](#). The regressions include time and household fixed effects. Heteroscedasticity-robust standard errors are shown in parentheses. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

In our benchmark analysis, we calculate bank characteristics for households reporting a cooperative bank relationship as a weighted average of all cooperative banks in their administrative region.¹¹ In the following robustness check, we eliminate noise from imprecisely identified bank relations by restricting our sample to customers of *savings* banks. Table 4, column (5), shows that our benchmark results remain statistically significant. In column (6), we also exclude all regions with more than one savings bank. The coefficient on the triple interaction term Post x Income x Bank exposure remains negative and economically comparable to the earlier specifications, but loses some of its statistical significance, likely due to the shrinking sample size. Together, columns (5)-(6) suggest that imprecision in the match between households and banks does not contaminate our analysis.

Competition and Alternative Credit Growth

In columns (7)-(8), we assess if regional bank presence, which might be related to competition among regional banks, affects our results. To do so, we split the sample into two sub-samples: one with regional bank presence below the median (computed as the sum of cooperative and savings banks active in the region) and one above it. Our results are clearly driven by regions with a higher presence of regional banks, suggesting that cross-border inflows only raise low-income households' access to consumer credit in regions with stronger presence of regional banks.

To check the sensitivity of our findings to the particular definition of credit growth, we next employ an alternative transformation of our main outcome variable, the inverse hyperbolic sine, that allows for including zero values. Column (9) shows that doing so has no effect on the significance of our coefficient estimates.¹²

¹¹We do the same for the few regions with more than one savings bank.

¹²Instead of computing the outcome variable as $\Delta \log(1 + x)$ so as to keep zero-valued observations, we apply an inverse hyperbolic sine ("arcsinh") transformation before computing the difference in consumer credit volumes between the different waves. This follows Bellemare and Wichman (2020), who argue that it both approximates the natural logarithm and is defined at zero.

Switching Behavior

As mentioned earlier, we observe a household’s main bank only in the two pre-inflow waves. Our empirical strategy thus implicitly assumes that an unobserved rise in switching behavior from regional to national banks, possibly with a greater lending capacity, between waves two and three does not drive our findings. Generally, German households are very loyal to their banks; only 117 households, or 7%, change their main bank between the first and second wave. Thus, we also do not expect substantial switching behavior between the second and third waves. To mitigate any residual concerns about an unobservable switching effect, we test if households with a greater tendency to switch in ”normal” times are driving our main findings. In Table 5, we exclude all households that changed their main bank between waves one and two and re-estimate our benchmark regression. Column (1) shows this reduces the size of our measured effect somewhat but maintains the significance of our coefficient.

Alternative Controls For Credit Demand

In columns (2) and (3), we conduct two additional sensitivity tests of our benchmark findings and control in a more granular way for potential shifts in the demand for credit. In column (2), we exclude households that were unemployed before the capital inflows from the estimation of Equation 2, while in column (3) we exclude self-employed households. Unemployed households are more likely to have little or no consumer credit initially and may therefore be more inclined to experience a rise in credit if they, for example, gain employment during the period of increased foreign bank inflows. Including such households in the benchmark regressions might consequently tilt our coefficient estimate towards finding a significant effect on household credit. Column (2) of Table 5 shows that this is an unwarranted concern as the coefficient estimate is more or less unchanged when unemployed households are excluded from the regression. Self-employed households, conversely, may experience a greater rise in credit during the post-inflow period if the inflows boosted general economic activity and increased credit demand, effects not fully captured by our fixed effects.

Table 5 ROBUSTNESS & HETEROGENEITY: BANK SWITCHING, CREDIT DEMAND, RELATIONSHIP LENGTH, CREDIT TYPE

	(1) No switchers	(2) No UI	(3) No self-employed	(4) Age ≥ 30	(5) Age ≥ 40	(6) No student loans	(7) Formal credit	(8) Triple bank interactions
Post \times Income	102.1 (88.29)	61.39 (100.4)	188.8* (101.3)	160.0* (84.31)	88.31 (86.97)	97.10 (85.11)	99.37 (85.25)	921.4 (594.3)
Post \times Non-Core	172.1*** (64.04)	157.5** (71.87)	202.9*** (68.99)	178.7*** (61.97)	150.1** (68.23)	150.2** (64.52)	152.4** (64.65)	203.7*** (70.01)
Post \times Income \times Non-Core	-11.56* (6.278)	-15.25** (7.244)	-20.06*** (6.673)	-18.65*** (5.884)	-14.56** (6.069)	-15.15** (5.921)	-15.27** (5.926)	-17.73** (6.986)
Household FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other Bank Interactions	No	No	No	No	No	No	No	Yes
Obs	1,302	1,264	1,090	1,488	1,380	1,536	1,534	1,534
R^2	0.311	0.306	0.308	0.295	0.308	0.313	0.313	0.328

NOTE. The dependent variable is the household-level change in the logarithm of consumer credit volumes. These regressions are based on the PHF data. Bank exposure variables originate from BISTA and GuV. The main regressors are the triple interactions between a Post-dummy equal to one for the third wave of the PHF survey and zero otherwise, bank-level NCFRs measured in wave 2, and the following household-level characteristics fixed at the wave 2 value: log of income, log of net wealth, a dummy measuring whether a household rents the main residence, age of the household head, a dummy for foreign citizenship, and income expectations. In column (1), we drop households that switched their main bank between wave 1 and 2. Column (2) drops unemployed, column (3) drops self-employed households. In columns (4) and (5), we drop households aged below 30 or 40, respectively. Columns (6) and (7) use a tighter definition of consumer credit, excluding student loans and loans from friends. In column (8), we control for the corresponding triple interactions between the Post-dummy, the aforementioned household characteristics, and the following additional bank covariates: bank size, capitalization, liquidity, and return on assets. Most interaction estimates are not displayed to conserve space. Data details can be found in Table A1. The regressions include time and household fixed effects. Heteroscedasticity-robust standard errors are shown in parentheses. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Relationship Length

This could also tilt our regressions towards finding a significant effect on lending to households. Column (3) confirms that when excluding self-employed households, the coefficient on the triple interaction term remains negative and significant at the 1% level. As noted earlier, our bank-level analysis assumes that households obtain their loans from their main relationship bank. This assumption is supported by [Puri et al. \(2017\)](#), who find that German households have very strong ties with their savings banks. They show that over 80 % of loan applicants have been customers for at least five years. Previous bank–depositor relationships also increase access to uncollateralized credit, such as consumer loans. To provide further support for this notion, we restrict our sample and run separate regressions for relatively older households, i.e., those who are likely to have longer-standing bank relationships. Columns (4) and (5) of Table 5 confirm that when we restrict our sample to households aged 30 years or more, and 40 years or more, respectively, the coefficient estimates are nearly the same as in the benchmark regressions.

Different Credit Types

Finally, we account for the fact that some sources of credit are unaffected by fluctuations in cross-border bank funding. The PHF’s definition of consumer loans includes consumer installment loans, bank overdrafts, credit card debt, loans from friends or employers, and student loans. As the latter two components are independent of bank loan supply, we redefine consumer credit more strictly by excluding loans from friends or employers, and student loans. Because the PHF, unfortunately, combines consumer installment loans and employer loans into one variable, we exclude only student loans in column (6). In column (7), we then remove households that report having obtained loans from their employer. Neither modification affects the estimated coefficient, although the significance level is slightly reduced as the sample size shrinks.

Controlling for Non-Random Treatment

A potential threat to our main regressions is that banks' exposure to cross-border flows may not be distributed randomly but correlates with other bank characteristics. As Table A2 shows, however, this is unlikely to be a major concern for our analysis as both more and less exposed banks share similar characteristics. Specifically, both types of bank types are comparable in size, profitability and capitalization. Only liquidity ratios seem to be significantly smaller for more exposed banks.

Yet, as explained in Section 4.1, controlling for these bank covariates increases the likelihood that the conditional mean zero assumption is satisfied and that we hence obtain unbiased estimates (Roberts and Whited, 2013). To this end, we run additional regressions that control for the triple interactions between a rich set of bank covariates, fixed at their pre-inflow wave 2 values, the post-dummy and our household covariates. Column (8) of Table 5 shows that their inclusion changes neither the size nor the significance of our coefficient of interest. While we do not report the coefficients for the additional interaction terms in Table 5, most of them are statistically insignificant. We do find, however, that following the bank inflow shock, better capitalized banks increase consumer lending to younger, high net worth households and those with foreign citizenship.

5.3 Placebo Test

In Section 4.1 we performed an initial check of the parallel trends assumption. Figure 3 indicated that more and less exposed banks exhibited lending patterns up to 2014 and diverged, particularly for lending to lower income households, when bank flows into Germany began increasing in 2014. Ideally, our survey data would contain a long pre-treatment time series for each household to verify if the parallel trends assumption is satisfied. Given that the PHF data span only three waves, we instead address this limitation by conducting placebo regressions. The first one estimates equation 2 on a pre-inflow sample. For this, we re-run our benchmark regression, restricting the data to the first (2010-2011) and second (2014)

survey waves. With only two sample waves, we cannot compute the outcome variable in log-differences, instead, we use the logarithm of consumer credit as the dependent variable. Column (1) of Table 6 confirms that that our main results hold when we re-run the benchmark regression with this alternative transformation of the credit variable. We then estimate this regression specification on the *pre-inflow* sample. Column (2) shows that, in this placebo regression, the difference in lending patterns between more and less exposed banks disappears. This finding provides additional support for the parallel trends assumption, suggesting that affected and unaffected banks followed similar lending paths before the sudden rise in international bank inflows.

Next, we perform two additional sets of placebo regressions to confirm that affected and unaffected banks displayed similar lending trends before the bank inflow shock. First, we run our benchmark regression with the log-change in consumer credit as the outcome variable but substitute the bank exposure variable with a placebo—the bank-level share of tangible fixed assets over total assets. Cross-border bank inflows provide additional liquidity to banks dependent on non-core funding, regardless of their asset structure, and in particular independently of the share of a bank’s tangible assets. We therefore expect this regression to produce insignificant treatment effects. Column (3) of Table 6 confirms that the consumer credit supply by “placebo-treated” and “untreated” banks evolves equally, further validating the parallel pre-trend assumption.

Second, instead of using a placebo treatment variable, we replace the dependent variable with household-level outcomes expected to be unrelated to cross-border bank flows. These include growth in income, growth of net worth, changes in the share of stocks in the asset portfolio, changes in the share of housing in total assets, and changes in housing tenure status. Columns (4)-(8) show that the triple interaction coefficient on Post x Income x NCFR is statistically insignificant for all these regressions. Households with relationships with more or less exposed banks exhibited no diverging dynamics in these placebo outcomes, providing further support for the parallel trend assumption.

Table 6 PLACEBO TESTS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Benchmark Ln(ConsLoans)	Placebo Ln(ConsLoans)	Δ Ln(ConsLoans)	Δ Ln(Income)	Δ Ln(NetWorth)	Δ Stocks	Δ Housing	Δ Tenure
Post \times Income	0.0301	-0.0729	37.17	19.60**	-21.92	-0.306	3.206	-0.0959***
	(0.386)	(0.500)	(26.28)	(8.014)	(15.62)	(0.37)	(3.1)	(0.0366)
Post \times Tangible			-162.3					
			(586.6)					
Post \times Income \times Tangible			32.72					
			(47.54)					
Post \times Non-Core	0.427	0.180		-1.698	-6.521	0.49	-0.0647	-0.0004
	(0.283)	(0.307)		(12.84)	(17.18)	(0.85)	(4.993)	(0.0482)
Post \times Income \times Non-Core	-0.0453*	0.0163		0.5	2.443	-0.0769	0.161	-0.0026
	(0.0275)	(0.0322)		(1.191)	(1.534)	(0.0731)	(0.471)	(0.0044)
Household FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	2,910	1,958	1,536	1,494	1,468	1,536	1,536	1,536
R^2	0.702	0.694	0.29	0.541	0.462	0.383	0.39	0.5

NOTE. These regressions are based on the PHF data. Bank exposure variables originate from BISTA and GuV. The dependent variable is the household-level change in the logarithm of consumer credit volumes (columns 1, 2, and 3), the log-change in income (column 4), the log-change in net worth (column 5), the change in the share of stocks over a household's total portfolio value (column 6), the change in the share of housing wealth over the total portfolio value (column 7) and the change in a household's housing tenure status (column 8). When a household reports zero stock or housing wealth, we set the portfolio share equal to zero. Housing tenure equals 1 when a household first rents the main residence and then owns it; zero when tenure status does not change; minus one when a household first owns and then rents its main residence. The main regressors are the triple interactions between a Post-dummy equal to one for the third wave of the PHF survey and zero otherwise, bank-level NCFRs (columns 1 and 2 and 4 to 8) or bank-level tangible fixed assets over total assets (column 3) measured in wave 2, and the following household-level characteristics fixed at the wave 2 value: log of income, log of net wealth, a dummy measuring whether a household rents the main residence, age of the household head, a dummy measuring whether a household has a migrant background, and income expectations. Most interaction estimates are not displayed to conserve space. Data details can be found in Table A1. The regressions include time and household fixed effects. Heteroscedasticity-robust standard errors are shown in parentheses. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

5.4 External Validity: Euro Area Households

Thus far, we have established that German households benefited from increased cross-border bank inflows. In this section, we show that our main findings have external validity in a larger data set for households from seven euro area countries. As explained above, these data do not contain a link between households and their banks. Therefore, we focus on the effect of cross-border bank inflows on credit volumes, without differentiating between more and less exposed banks. Instead, we measure households' exposure by means of *country*-level bank inflows over GDP, as displayed in Figure 2.

In Table 7, we present evidence that other euro area countries besides Germany also experienced a rise consumer credit to low-income households as cross-border bank flows into these countries grew. In column (1), we estimate Equation 3 on the largest possible data set, excluding the foreign citizenship dummy missing for Spain. Consumer credit to low-income households increases significantly in countries that experience greater cross-border bank inflows, as can be seen from the implied t-statistics for the triple interaction term: Post x country-level bank inflows x household income.

Our coefficient of interest remains consistent when we replicate the German regression controls as closely as possible by including the foreign citizenship dummy (column 2) and country-time fixed effects (column 3). In column (4), we isolate the log-income triple interactions while omitting other household interactions, still obtaining a significant coefficient estimate. Similarly, the results hold in column (5), where we exclude the 5,546 German households that were included in columns (1)-(4), though in this case the triple interaction coefficient falls slightly below conventional significance levels. Finally, in column (6), we use the log of mortgage credit volumes as the outcome variable. Consistent with our German benchmark results, we do not see a shift in mortgage credit across households.

Table 7 RESULTS FOR THE EUROPEAN HOUSEHOLD SAMPLE

	(1)	(2)	(3)	(4)	(5)	(6)
	Ln(ConsLoans)	Ln(ConsLoans)	Ln(ConsLoans)	Ln(ConsLoans)	Ln(ConsLoans)	Ln(Mortgages)
Post \times Income	-0.197** (0.08)	-0.134** (0.05)	-0.122** (0.04)	-0.089* (0.04)	-0.170* (0.08)	-0.059 (0.01)
Post \times Income \times Flows	-0.034* (0.02)	-0.027* (0.01)	-0.035** (0.01)	-0.025*** (0.01)	-0.026 (0.02)	-0.019 (0.02)
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-Time FE	No	No	Yes	No	No	No
Household Controls \times Post \times Flows	Yes	Yes	Yes	No	Yes	Yes
Obs	34,980	28,270	34,980	35,034	29,434	34,980
No. of Countries	7	6	7	7	6	7
R^2	0.726	0.735	0.727	0.725	0.727	0.873

Note: The regressions are based on waves 2 and 3 of the HFCS survey. The dependent variable in columns (1)-(5) is the logarithm of consumer loans. In column (6), it is the logarithm of mortgages. The main regressor is country-level net bank inflows over nominal GDP, averaged during 2016-2017, and interacted with household-level income measured in wave 2 as well as a dummy equal to one after the significant change in bank flows (wave 3) and zero otherwise. All columns, apart from column (4), include time and household fixed effects and the following household controls, measured in wave 2, interacted with the Post-dummy and country-level bank flows: net worth, age, and a renter dummy. Only column (2) includes additionally a dummy for foreign citizenship. All these interactions, as well as all lower-order interactions of the triple interactions, are included in all regressions unless they are absorbed by fixed effects, but we suppress their coefficients to save space. Column (3) additionally controls for country-time fixed effects. Standard errors, clustered at the country-time level, are shown in parentheses. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Taken together, the results in Table 7 provide evidence that other euro area countries exhibited a similar increase in consumer credit towards low-income households in response to the inflow of foreign bank funding. The results also demonstrate that the findings for German households were not driven by the ECB’s non-conventional monetary policy, as all euro area countries faced the same monetary policy mix. Only euro area countries with greater bank inflows experienced a shift in consumer credit towards low-income households.

6 Mechanisms

In this section, we identify the mechanisms underlying our results. We start by examining whether the *aggregate* bank inflow shock indeed implies higher *bank-level* non-core funding volumes for more relative to less exposed banks. Then we study to what extent our results are driven by regional banks obtaining interbank liquidity from abroad directly, or whether cross-border interbank liquidity trickles down to regional German banks through large banks. Next, we study the extensive versus the intensive margin of lending. Finally, we investigate why banks especially raise their consumer loan supply to low-income, higher-risk households, with a particular focus on the role of bank agency problems.

6.1 More Exposed Banks Experience Greater Funding Inflows

Our main regression specification implicitly assumes that banks with higher initial non-core funding ratios are more exposed to aggregate bank inflow shocks. In this sub-section, we verify this assumption by examining whether these banks indeed experience greater non-core funding inflows from abroad following the shock.

To investigate this, we regress the logarithm of each bank’s total non-core funding volume as well as the interbank component individually on the interaction term $\text{Post} \times \text{NCFR}$, using the same sample period as in the household regressions. We include bank and year fixed effects and cluster standard errors at the bank level. As Table 8 shows, banks with a

higher NCFR prior to the cross-border bank inflow shock indeed experience higher non-core funding inflows, regardless of whether measured as total non-core funding (column 1) or as interbank liabilities (column 2). These effects are approximately twice as large when focusing exclusively on regional banks (columns 3-4), consistent with the household regression findings. Together, these results confirm that banks classified as more exposed are indeed the ones experiencing higher inflows of wholesale funds as a consequence of the cross-border inflow shock.

Table 8 DO NON-CORE VOLUMES INCREASE FOR MORE EXPOSED BANKS?

	All Banks		Regional Banks	
	(1)	(2)	(3)	(4)
	Ln(Noncore)	Ln(Interbank)	Ln(Noncore)	Ln(Interbank)
Post \times Non-Core	0.003*** (0.001)	0.003*** (0.001)	0.006*** (0.002)	0.005** (0.002)
Bank FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Obs	14,212	14,212	11,735	11,735
R^2	0.96	0.95	0.98	0.97

NOTE. The dependent variable is the log-level of a bank's non-core or interbank funds, respectively. The data originate from BISTA and GuV and cover the period 2010-17. The main regressor is the double interaction between a Post-dummy equal to one for the third wave of the PHF survey and zero otherwise, and bank-level NCFRs measured in wave 2. In columns (1) and (2), we include all banks in the analysis. Columns (3) and (4) only include regional banks. Data details can be found in Table A1. Time and bank fixed effects are included. Heteroscedasticity-robust standard errors clustered at the bank level are shown in parentheses. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% level.

6.2 Direct vs Indirect Transmission

So far, we have shown that regional banks dependent on non-core funding increase their consumer lending to low-income households. This could be driven either by direct access to foreign wholesale liquidity or by a trickle-down effect, where larger banks attract cross-border bank inflows and pass on their liquidity "surplus" to smaller banks. To disentangle both effects we exploit the granularity of the supervisory data, which allows us to break down

interbank deposits—the largest component of banks’ non-core funding—into its domestic, euro area, and non-euro area parts.¹³ If our benchmark results are driven by a trickle-down mechanism, we would expect the triple interaction with domestic interbank deposits to be significant, whereas the triple interactions for the foreign components should not exhibit significance. In contrast, if a direct pass-through from foreign to regional banks is behind our results, the foreign interbank deposit interactions should be significant.

Columns (1)-(3) of Table 9 show that the coefficients on both domestic and non-euro area interbank deposits are statistically significant, but that on within-euro area interbank deposits is not. Economically, the impact of non-euro interbank deposits on bank lending to low-income households dominates that of German interbank deposits, with the normalized coefficient on non-euro area deposits being five times greater. This suggests that our results are primarily driven by direct deposits from non-euro area banks into regional German banks, with amplification through a trickling down of funds deposited at large, nationally active banks. Our analysis is limited to inflows and outflows at German banks due to data constraints, preventing further investigation into the negligible role of euro area interbank deposits in the transmission mechanism. Euro area banks accounted for only roughly 7% of inflows into Germany during 2015-2017. In contrast, inflows from the UK into Germany were on average eight times larger than those from France and seven times larger than flows from the Netherlands. This disparity may reflect the strong ties between large global, non-euro area banks and the German banking system or regional portfolio preferences.

¹³This breakdown is not available for the other variables used in the construction of non-core ratios. We standardize all three variables by subtracting the mean and dividing by the standard deviation to make the associated results comparable to each other.

Table 9 MECHANISMS: FUNDING SOURCES, EXTENSIVE MARGIN AND BANK CAPITAL

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$\Delta \text{Ln}(\text{ConsLoans})$	$\Delta \text{Ln}(\text{ConsLoans})$	$\Delta \text{Ln}(\text{ConsLoans})$	$\text{Prob}(\text{NewLoan})$	$\text{Prob}(\text{MoreCred})$	Low-Cap $\Delta \text{Ln}(\text{ConsLoans})$	High-Cap $\Delta \text{Ln}(\text{ConsLoans})$
Post \times Income	-96.06** (40.56)	-94.01** (41.26)	-117.8*** (41.96)	3.01 (5.27)	-1.73 (5.13)	293.3*** (72.58)	-39.55 (155.7)
Post \times Exp.				6.31* (3.82)	0.718 (3.55)	235.3*** (72.58)	143.4 (117.2)
Post \times Income \times DE Exp.	-90.06*** (34.78)						
Post \times Income \times EA exp.		-67.8 (62.75)					
Post \times Income \times Non-EA exp.			-521.4** (236.9)				
Post \times Income \times Exp.				-0.607* (0.362)	0.00 (0.364)	-26.29*** (6.907)	-6.630 (11.55)
Household FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	1,536	1,536	1,536	1,502	1,502	784	752
R^2	0.296	0.289	0.291	0.454	0.545	0.333	0.295

NOTE. Regressions are based on the PHF data. Bank exposure variables originate from BISTA and GuV. The dependent variable is the household-level change in the logarithm of consumer credit volumes (columns 1-3, 6-7), a dummy equal to one when a household had zero consumer credit in the pre-period, but a positive value in the post-period (column 4), and a dummy equal to one when a household had positive consumer credit in the pre-period and consumer credit was higher in the post-period (column 5). Coefficients in columns (4-5) have been multiplied by 100 and thus reflect marginal changes in the percentage probability of granting credit. The main regressors are the triple interactions between a Post-dummy equal to one for the third wave of the PHF survey and zero otherwise, bank-level exposure measured in wave 2, and the following household-level characteristics fixed at the wave 2 value: log of income, log of net wealth, a dummy equal to one if a household rents the main residence, age of the household head, a dummy measuring if a household head has foreign citizenship, and income expectations. Most interaction estimates are not displayed to conserve space. As measure of exposure, column (1) uses a bank's domestic interbank deposit ratio, column (2) a bank's euro area interbank deposit ratio, column (3) a bank's non-euro area interbank deposit ratio and columns (4)-(7) the NCFR. In columns (6) and (7), we split the sample into low-capitalized banks (below median) and well-capitalized banks (above median). Data details are available in Table A1. The regressions include time and household fixed effects. Heteroscedasticity-robust standard errors are shown in parentheses. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

6.3 Intensive vs Extensive Margin

Next, we investigate the extent to which our key result that more exposed banks raise consumer lending to low-income households is driven by changes in the intensive or extensive margin of lending. For this purpose, we compute the credit variables as (i) a dummy that equals one if consumer loans were zero in the pre-inflow period and positive during the period of large inflows and zero otherwise, and (ii) a second dummy equal to one if consumer loans were already positive in the pre-period but grew during the post-period and zero otherwise. We then run regressions on these dummy variables using OLS. Table 9, column (4), shows that more exposed banks expand their lending to low-income households along the extensive margin. The coefficient estimate on the triple interaction term is negative, as in prior results, and is statistically significant at the 10% level. This estimate implies that treated relative to non-treated banks are 4.4% more likely to give credit to new borrowers in the 75th percentile of the income distribution than to those in the 25th percentile of the income distribution. We obtain similar results when we apply a probit or logit model. The extensive margin thus plays an important role in the overall credit increase, suggesting that households with initially limited access to credit saw these constraints loosen following the rise in bank inflows. In contrast, the intensive margin does not play a role, as indicated by the insignificant estimate in column (5).

6.4 Bank Capitalization

Why do more exposed banks raise their consumer lending to higher-risk rather than to lower-risk borrowers? The existing literature on the risk-taking channel of both monetary policy and capital flow transmission suggests that poorly capitalized banks tend to engage (more) in riskier lending (e.g., [Jiménez et al., 2014](#); [Altavilla et al., 2020](#); [Dinger and Te Kaat, 2020](#); [Te Kaat, 2021](#)). The theoretical rationale underlying this empirical result is that bank agency problems become more severe as banks' capitalization falls, because banks fail to fully internalize the consequences of a potential default. As a consequence, they are less likely

to screen and monitor borrowers intensively ([Holmstrom and Tirole, 1997](#)). To investigate whether our findings are driven by poorly capitalized banks, we re-estimate our benchmark regression on two sub-samples: one that consists of banks with a capital-to-asset ratio below the in-sample median and another that is composed of above-median banks.

Columns (6) and (7) of Table 9 show that only poorly capitalized banks more exposed to cross-border flows raise their consumer lending to low-income households after the bank inflow shock. The coefficient estimate is 1.5-2 times larger than our benchmark estimate in Table 3, implying a credit growth differential of 189 percentage points between low- and high-income households borrowing from more exposed versus less exposed banks. In contrast, we do not find a shift in more exposed banks' consumer lending towards low-income households for the sub-sample of well-capitalized banks. Our analysis thus documents that the transmission of foreign capital inflow shocks to households through bank funding operates via similar risk-taking channel as earlier research has reported for monetary policy transmission and firm funding.

7 Real Effects of Local Credit Booms

Having established that German households experienced a growth in their consumer credit following a rise in cross-border bank inflows, we next investigate the real effects of households' improved credit access. In particular, we are interested in understanding if households benefiting more from the increase in consumer lending raise their consumption relative to other households. To this end, we re-estimate equation 2 using the logarithm of non-durable or durable consumption as the outcome variable. For expenses on non-durable consumption, we can further differentiate between two distinct components: expenses on food and drinks at home, or, alternatively, outside households' home. We will subsequently refer to these categories as "food" and "restaurant".

In Table 10, we first look at a plain regression that highlights treatment effects by house-

Table 10 BANK FLOWS, CREDIT AND CONSUMPTION EFFECTS

	(1) Non-durable	(2) Durable	(3) Food	(4) Restaurant
Post \times Income	-0.0411 (0.0251)	-0.0151 (0.0677)	-0.0158 (0.0203)	-0.134 (0.0839)
Household FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Obs	2,910	2,674	2,910	2,910
R^2	0.741	0.654	0.813	0.772

NOTE. Regressions are based on the PHF data. Bank exposure variables originate from BISTA and GuV. The dependent variable is the household-level logarithm of durable, non-durable, food and restaurant consumption. The main regressors are double interactions between a Post-dummy equaling one for wave 3 of the PHF survey and zero otherwise, and the following household-level variables fixed at the wave 2 value: log (income), log(net wealth), a dummy for households rent their main residence, age of the household head, a dummy foreign citizenship, and income expectations. Most interaction estimates are suppressed to conserve space. Data details can be found in Table A1. Regressions include time and household fixed effects. Heteroscedasticity-robust standard errors are shown in parentheses. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% levels.

hold income. Then, in Table 11 we split our sample into households borrowing from banks with low versus high NCF ratios to determine whether consumption changes are consistent across the board or confined to households linked to more exposed banks. All regressions include household and time fixed effects, as well as household controls interacted with the Post-dummy. Table 10 shows that low-income households indeed increase consumption expenditures following the bank inflow shock. However, the coefficient estimates are weakly identified and not statistically significant. This is consistent with our findings in Table 3, which showed that only low-income households borrowing from exposed banks experienced a rise in credit.

Table 11 BANK FLOWS AND CONSUMPTION: DISTINGUISHING BY BANK EXPOSURE

	Less Exposed Banks				More Exposed Banks			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Non-durable	Durable	Food	Restaurant	Non-durable	Durable	Food	Restaurant
Post \times Income	-0.0225 (0.0383)	-0.0320 (0.119)	0.00984 (0.0330)	-0.0500 (0.158)	-0.0553* (0.0322)	-0.00768 (0.0815)	-0.0316 (0.0254)	-0.177* (0.0992)
Household FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	950	874	950	950	1,960	1,800	1,960	1,960
R^2	0.751	0.680	0.838	0.781	0.738	0.648	0.803	0.769

NOTE. The dependent variable is the household-level logarithm of durable, non-durable, food and restaurant consumption. The main regressors are the double interactions between a Post-dummy equal to one for the third wave of the PHF survey, zero otherwise, and the following household-level characteristics fixed at the wave 2 value: log of income, log of net wealth, a dummy measuring whether a household rents the main residence, age of the household head, a dummy measuring whether a household has a migrant background, and income expectations. Most interaction estimates are not displayed to conserve space. Data details can be found in Table A1. In columns (1)-(4), we focus on households whose main relationship is with a less exposed bank (lowest 33% of non-core distribution) and in columns (5)-(8), we focus on more exposed banks (upper 67%). The regressions include time and household fixed effects. Heteroscedasticity-robust standard errors are shown in parentheses. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

We proceed by splitting the sample into households borrowing from more exposed and less exposed banks, i.e., those with higher and lower non-core ratios. Columns (1)-(4) in Table 11 show that households borrowing from less exposed banks do not increase consumption. Low-income households banking with more exposed credit providers do, however, show an increase in their non-durable consumption, particularly food and beverages consumed outside the home (columns (5)-(8)), although the coefficients in columns (1)-(4) are not statistically different from those in columns (5)-(8). Durable consumption by low-income households, on the other hand, is not affected by bank inflows. The effect on non-durable consumption is not only statistically, but also economically significant. After the shock, a low-income household, i.e., one in the 25th percentile of the income distribution, has a 28.7% higher consumption of non-durables relative to their pre-inflow consumption, and relative to a higher-income household, i.e. one in the 75th percentile of the income distribution.

Overall, these findings provide valuable insights into the effects of international capital flows. While cross-border bank inflows have been shown to bear the potential of financial instability risks through sudden increases in lending, our analysis highlights their role in relaxing credit constraints for poorer households with previously unmet demand for credit. The improvement in their access to credit translates exclusively into a growth of shorter-term consumer credit, which these households use to raise non-durable consumption, a more transitory form of expenditure.

8 Conclusions

We study the effects of cross-border capital flows on regional German banks' risk-taking and their credit supply to households. We employ granular matched bank-household data and establish that cross-border bank inflows induce regional banks with a greater non-core funding dependency to increase their uncollateralized lending to riskier, lower-income households. However, we do not observe any increase in risk-taking in banks' mortgage lending.

When investigating through which channels foreign funding flows affect lending, we find that the rise in credit by regional German banks occurred through funding inflows from primarily non-euro area banks and to a lesser extent through interbank funding from other German banks. Consistent with the presence of a risk-taking channel similar to that in earlier research on the transmission of monetary policy, we establish that worse capitalized banks are responsible for the rise in credit, while better capitalized banks show no growth in household lending. We further demonstrate that this credit expansion occurs through the extensive margin. Finally, as access to credit improves, lower-income households who are clients of more exposed banks increase their consumption expenditures, especially on non-essential non-durables. We establish the external validity of our main results using cross-country household data from almost 18,000 households in the euro area.

While previous research has shown that cross-border capital inflows raise banks' lending to risky *firms*, we provide new household-level evidence that a similar risk-taking effect exists in banks' *household* lending. We also document that cross-border capital flows generate large fluctuations in credit supply through smaller regional banks in Germany, an advanced economy and the largest member state of the euro area.

Other research has recently demonstrated that particularly credit booms in the household sector can lead to boom-bust cycles and predict financial crises. A rise in credit may thus raise financial stability risks. At the same time, greater access to credit allows lower-income households to increase consumption and therefore reduce consumption inequality, at least in the short run. In the longer run, however, poorer households will face increased debt levels.

Overall, our analysis highlights the trade-offs policymakers face when foreign capital inflows in the interbank market lead to fluctuations in the availability of credit. A complete assessment of the *long-term* effects of cross-border capital inflows on (consumption) inequality and a granular understanding of the mechanisms behind these effects requires further research.

References

- Acharya, Viral and Hassan Naqvi**, “The seeds of a crisis: A theory of bank liquidity and risk taking over the business cycle,” *Journal of Financial Economics*, 2012, *106* (2), 349–366.
- Altavilla, Carlo, Luc Laeven, and José-Luis Peydró**, “Monetary and Macroprudential Policy Complementarities: evidence from European credit registers,” *ECB Working Paper No. 2504*, 2020.
- American Express**, “Average Credit Scores by Age, State, and Income,” Technical Report December 2022.
- Baskaya, Yusuf Soner, Julian di Giovanni, Şebnem Kalemli-Özcan, José-Luis Peydró, and Mehmet Fatih Ulu**, “Capital flows and the international credit channel,” *Journal of International Economics*, 2017, *108*, S15–S22.
- Beer, Rachael, Felicia Ionescu, and Geng Li**, “Are Income and Credit Scores Highly Correlated?,” FEDS Notes 2018-08-13-1, Board of Governors of the Federal Reserve System (U.S.) August 2018.
- Bellemare, Marc F and Casey J Wichman**, “Elasticities and the inverse hyperbolic sine transformation,” *Oxford Bulletin of Economics and Statistics*, 2020, *82* (1), 50–61.
- Bergant, Katharina, Michael Fidora, and Martin Schmitz**, *International capital flows at the security level: evidence from the ECB’s asset purchase programme*, International Monetary Fund, 2020.
- Blanc, Julia Le and Tobias Schmidt**, “Estimating household consumption using wealth survey data,” *Mimeo, Deutsche Bundesbank*, 2018.
- Caballero, Julián A**, “Do surges in international capital inflows influence the likelihood of banking crises?,” *Economic Journal*, 2016, *126* (591), 281–316.

- Campbell, John Y. and Joao F. Cocco**, “A Model of Mortgage Default,” *Journal of Finance*, 2015, 70 (4), 1495–1554.
- Cetorelli, Nicola and Linda S. Goldberg**, “Banking Globalization and Monetary Transmission,” *Journal of Finance*, 2012, 67 (5), 1811–1843.
- Correa, Ricardo, Teodora Paligorova, Horacio Sapriza, and Andrei Zlate**, “Cross-Border Bank Flows and Monetary Policy,” *Review of Financial Studies*, 02 2021, 35 (1), 438–481.
- Degryse, Hans, Olivier De Jonghe, Sanja Jakovljević, Klaas Mulier, and Glenn Schepens**, “Identifying credit supply shocks with bank-firm data: Methods and applications,” *Journal of Financial Intermediation*, 2019, 40, 100813.
- di Giovanni, Julian, Şebnem Kalemli-Özcan, Mehmet Fatih Ulu, and Yusuf Soner Baskaya**, “International Spillovers and Local Credit Cycles,” *Review of Economic Studies*, 10 2021, 89 (2), 733–773.
- Dinger, Valeriya and Daniel Marcel te Te Kaat**, “Cross-border capital flows and bank risk-taking,” *Journal of Banking & Finance*, 2020, 117, 105842.
- Epure, Mircea, Irina Mihai, Camelia Minoiu, and José-Luis Peydró**, “Global financial cycle, household credit, and macroprudential policies,” *Forthcoming in: Management Science*, 2024.
- Garber, Gabriel, Atif Mian, Jacopo Ponticelli, and Amir Sufi**, “Household debt and recession in Brazil,” in “Handbook of US Consumer Economics,” Elsevier, 2019, pp. 97–119.
- Gyöngyösi, Győző, Steven Ongena, and Ibolya Schindele**, “The impact of monetary conditions on bank lending to households,” *SFI Working Paper*, 2024.

- Hale, Galina, Tümer Kapan, and Camelia Minoiu**, “Shock Transmission Through Cross-Border Bank Lending: Credit and Real Effects,” *Review of Financial Studies*, 2020, *33* (10), 4839–4882.
- Holmstrom, Bengt and Jean Tirole**, “Financial intermediation, loanable funds, and the real sector,” *Quarterly Journal of Economics*, 1997, *112* (3), 663–691.
- Iyer, Rajkamal and José-Luis Peydró**, “Interbank Contagion at Work: Evidence from a Natural Experiment,” *Review of Financial Studies*, 04 2011, *24* (4), 1337–1377.
- Jiménez, Gabriel, Steven Ongena, José-Luis Peydró, and Jesús Saurina**, “Hazardous times for monetary policy: What do twenty-three million bank loans say about the effects of monetary policy on credit risk-taking?,” *Econometrica*, 2014, *82* (2), 463–505.
- Jonghe, Olivier De, Hans Dewachter, Klaas Mulier, Steven Ongena, and Glenn Schepens**, “Some borrowers are more equal than others: Bank funding shocks and credit reallocation,” *Review of Finance*, 2020, *24* (1), 1–43.
- Jordà, Òscar, Moritz Schularick, and Alan M Taylor**, “When credit bites back,” *Journal of Money, Credit and Banking*, 2013, *45* (s2), 3–28.
- , —, and —, “The great mortgaging: housing finance, crises and business cycles,” *Economic Policy*, 2016, *31* (85), 107–152.
- Kaat, Daniel Te**, “Cross-border debt flows and credit allocation: Firm-level evidence from the euro area,” *Journal of Money, Credit and Banking*, 2021, *53* (7), 1797–1818.
- Khwaja, Asim Ijaz and Atif Mian**, “Tracing the impact of bank liquidity shocks: Evidence from an emerging market,” *American Economic Review*, 2008, *98* (4), 1413–1442.
- Kindermann, Fabian, Julia Le Blanc, Monika Piazzesi, and Martin Schneider**, “Learning about housing cost: Survey evidence from the German house price boom,” *NBER Working Paper 28895*, 2021.

- Kneer, Christiane and Alexander Raabe**, “Tracking foreign capital: the effect of capital inflows on bank lending in the UK,” *Bank of England Staff Working Paper No. 804*, 2019.
- Magud, Nicolas E, Carmen M Reinhart, and Esteban R Vesperoni**, “Capital inflows, exchange rate flexibility and credit booms,” *Review of Development Economics*, 2014, *18* (3), 415–430.
- Martinez-Miera, David and Rafael Repullo**, “Search for yield,” *Econometrica*, 2017, *85* (2), 351–378.
- Mayer, Erik J.**, “Big Banks, Household Credit Access, and Intergenerational Economic Mobility,” *Journal of Financial and Quantitative Analysis*, 2023, p. 1–37.
- Mian, Atif, Amir Sufi, and Emil Verner**, “Household debt and business cycles worldwide,” *Quarterly Journal of Economics*, 2017, *132* (4), 1755–1817.
- Müller, Karsten and Emil Verner**, “Credit allocation and macroeconomic fluctuations,” *Forthcoming in: Review of Economic Studies*, 2024.
- Ongena, Steven, Günseli Tümer-Alkan, and Natalja Von Westernhagen**, “Do exposures to sagging real estate, subprime, or conduits abroad lead to contraction and flight to quality in bank lending at home?,” *Review of Finance*, 2018, *22* (4), 1335–1373.
- , **José-Luis Peydró, and Neeltje van Horen**, “Shocks Abroad, Pain at Home? Bank-Firm-Level Evidence on the International Transmission of Financial Shocks,” *IMF Economic Review*, 2015, *63* (4), 698–750.
- Puri, Manju, Jörg Rocholl, and Sascha Steffen**, “What do a million observations have to say about loan defaults? Opening the black box of relationships,” *Journal of Financial Intermediation*, 2017, *31*, 1–15.

- , **Jörg Rocholl**, and **Sascha Steffen**, “Global retail lending in the aftermath of the US financial crisis: Distinguishing between supply and demand effects,” *Journal of Financial Economics*, 2011, *100* (3), 556–578.
- Rajan, Raghuram G**, “Has finance made the world riskier?,” *European financial management*, 2006, *12* (4), 499–533.
- Roberts, Michael R and Toni M Whited**, “Endogeneity in empirical corporate finance,” in “Handbook of the Economics of Finance,” Vol. 2, Elsevier, 2013, pp. 493–572.
- Saffie, Felipe, Liliana Varela, and Kei-Mu Yi**, “The micro and macro dynamics of capital flows,” Technical Report, National Bureau of Economic Research 2020.
- Sarmiento, Miguel**, “Sudden yield reversals and financial intermediation in emerging markets,” *Journal of Financial Stability*, 2022, p. 101050.
- Schaefer, M. and H. Stahl**, “Monthly Balance Sheet Statistics (BISTA), Data Report 2023-08 – Metadata Version BISTA-Doc-v5-0,” *Mimeo, Deutsche Bundesbank, Research Data and Service Centre*, 2023.
- Schnabl, Philipp**, “The International Transmission of Bank Liquidity Shocks: Evidence from an Emerging Market,” *Journal of Finance*, 2012, *67* (3), 897–932.
- Schularick, Moritz and Alan M Taylor**, “Credit booms gone bust: monetary policy, leverage cycles, and financial crises, 1870–2008,” *American Economic Review*, 2012, *102* (2), 1029–1061.
- Stahl, H. and N. Scheller**, “Statistics of the banks’ profit and loss accounts (GuV), Data Report 2023-06 – Documentation version 12,” *Mimeo, Deutsche Bundesbank, Research Data and Service Centre*, 2023.
- Sufi, Amir and Alan M Taylor**, “Financial crises: A survey,” *Handbook of International Economics*, 2022, *6*, 291–340.

Temesvary, Judit, Steven Ongena, and Ann L. Owen, “A global lending channel unplugged? Does U.S. monetary policy affect cross-border and affiliate lending by global U.S. banks?,” *Journal of International Economics*, 2018, *112*, 50–69.

Appendix

‘Cross-Border Bank Flows, Regional Household Credit Booms and Bank Risk-Taking’

by D. Boddin, D. te Kaat and K. Roszbach

December 17, 2024

A Additional Tables

Table A1 VARIABLE DEFINITIONS AND SOURCES

Variable	Definition	Unit	Source
Δ Consumerloans	The log-difference in households' outstanding consumer credit volumes	%	HFCS or PHF, respectively
Δ Mortgages	The log-difference in households' outstanding mortgage credit volumes	%	HFCS/PHF
Consumption(non-durable)	The logarithm of households' non-durable consumption	ln(x)	PHF
Consumption(durable)	The logarithm of households' durable consumption, defined as income less net saving less non-durable consumption	ln(x)	PHF
Consumption(food)	The logarithm of households' food at home consumption	ln(x)	PHF
Consumption(restaurant)	The logarithm of households' food outside home consumption	ln(x)	PHF
Net wealth	The logarithm of a household's net wealth (assets less liabilities)	ln(euro)	HFCS/PHF
Income	The logarithm of a household's total gross income	ln(euro)	HFCS/PHF
Renter	=1 if household is a renter in the main residence	0/1	HFCS/PHF
Foreign	=1 if a household's country of birth is outside of Germany	0/1	HFCS/PHF
Age	Age of the household head	-	HFCS/PHF
Income Exp.	=1 if a household expects its income to rise more than inflation	0/1	PHF
Self-Employed	=1 if a household generates self-employment income	0/1	PHF
Unemployed	=1 if a household receives unemployment benefits or any other regular social transfers	0/1	PHF
Non-Core	Banks' sum of interbank deposits, as well as money market securities and bonds issued, over total assets	%	Deutsche Bundesbank
Gross Interbank	Banks' interbank deposits over total assets	%	Deutsche Bundesbank
Gross Domestic Interbank	Banks' standardized domestic interbank deposits over total assets	%	Deutsche Bundesbank
Gross EA Interbank	Banks' standardized within-euro area interbank deposits over total assets	%	Deutsche Bundesbank
Gross Non-EA Interbank	Banks' standardized non-euro area interbank deposits over total assets	%	Deutsche Bundesbank
Net Interbank	Banks' interbank deposits net of interbank loans over total assets	%	Deutsche Bundesbank
Ln(Noncore)	Banks' logarithm of non-core funding volumes	ln(euro)	Deutsche Bundesbank
Ln(Interbank)	Banks' logarithm of interbank funding volumes	ln(euro)	Deutsche Bundesbank
Size	Bank size, defined as the log of total assets	ln(euro)	Deutsche Bundesbank
ROA	Banks' return on assets	%	Deutsche Bundesbank
ROE	Banks' return on equity	%	Deutsche Bundesbank
Liquidity	Banks' sum of cash, central bank reserves and treasuries held over total assets	%	Deutsche Bundesbank
Capitalization	Banks' total capital over total assets	%	Deutsche Bundesbank
Other flows	Net other investment inflows over nominal GDP	%	International Financial Statistics
Portfolio flows	Net portfolio investment inflows over nominal GDP	%	International Financial Statistics
FDI Flows	Net foreign direct investment inflows over nominal GDP	%	International Financial Statistics
Bank flows	FX and break-adjusted change in banks' liabilities less the equivalent change in assets vis-a-vis all other banks over GDP	%	BIS-LBS

Table A2 COMBINED SUMMARY STATISTICS: MORE AND LESS EXPOSED BANKS

Variable	More		Less	
	Observations	Mean	Observations	Mean
Δ Mortgages	1,050	.	486	-41.89
Δ Consumerloans	1,050	-34.18	486	-24.51
Consumption(non-durable)	1,050	9.29	486	9.22
Consumption(durable)	1,004	9.76	464	9.87
Consumption(food)	1,050	8.52	486	8.55
Consumption(restaurant)	1,050	6.42	486	6.54
Net wealth	1,050	12.06	486	12.02
Income	1,050	10.88	486	10.79
Renter	1,050	0.30	486	0.33
Age	1,050	59.45	486	60.27
Foreign	1,050	0.07	486	0.05
Income Exp.	1,050	0.07	486	0.09
Unemployed	1,050	0.29	486	0.28
Self-employed	1,050	0.18	486	0.17
Noncore	1,050	16.37	486	7.22
Gross Interbank	1,050	15.18	486	6.84
Gross Domestic Interbank	1,050	0.47	486	-0.96
Gross EA Interbank	1,050	0.16	486	-0.29
Gross Non-EA Interbank	1,050	-0.02	486	-0.03
Net Interbank	1,050	8.01	486	-1.73
Size	1,050	14.50	486	14.38
ROA	1,048	0.16	486	0.14
Equity	1,050	5.70	486	5.61
Liquidity	1,050	1.32	486	1.57

NOTE. The table reports summary statistics for the German bank-household data set for households with its main relationship with a more exposed bank (upper 67% of the non-core distribution) and less exposed bank (lowest 33% of the non-core distribution). The mean for Δ Mortgages cannot be displayed due to data confidentiality reasons. We provide data definitions and sources in Table [A1](#).

Table A3 SUMMARY STATISTICS FOR EUROPEAN HOUSEHOLDS: DIFFERENCES
BETWEEN MORE AND LESS EXPOSED COUNTRIES

Variable	Less Exposed Countries		More Exposed Countries	
	Observations	Mean	Observations	Mean
Ln(ConsLoans)	23,542	2.1	11,438	2.7
Ln(Mortgages)	23,542	2.9	11,438	4.0
Net wealth	23,542	12.1	11,438	12.0
Income	23,542	10.5	11,438	10.9
Renter	23,542	0.2	11,438	0.2
Household age	23,542	57.8	11,438	55.7
Foreign citizenship	16,832	0.1	11,438	0.1
Bank flows	23,542	-1.1	11,438	4.1

NOTE. The table reports summary statistics for the European HFCS sample, separately for countries with positive bank inflows during 2016-17 (more exposed countries) and those with negative bank inflows (less exposed countries). The summary statistics are reported for all households that are included in Table 7, column (1). We provide data definitions and sources in Section 2.2.

B Effect on Bank Profitability

In this section, we study whether the increase in more exposed banks' lending to low-income households affects their profitability. To this end, we employ annual bank-level data from 2010-17 and regress banks' return on assets or equity, respectively, on the interaction between the post-inflow dummy and banks' pre-shock non-core funding ratio.

Columns (1)-(2) of Table A4 include all banks in the analysis, and the attendant coefficient estimates are statistically insignificant throughout. In columns (3)-(4), we only focus on savings and cooperative banks, as in the household-level analysis. In this case, the double interaction of interest turns out as being positive and statistically significant at least at the 10% level. This is suggestive evidence that the consumer credit reallocations have a positive effect on the profitability of regional banks.

Table A4 EFFECTS ON BANK PROFITABILITY

	All Banks		Regional Banks	
	(1)	(2)	(3)	(4)
	ROA	ROE	ROA	ROE
Post \times Non-Core	-0.002 (0.002)	0.004 (0.025)	0.001** (0.000)	0.012* (0.007)
Bank FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Obs	13,242	13,242	11,549	11,549
R^2	0.82	0.91	0.83	0.73

NOTE. The dependent variable is a bank's return on assets or equity, respectively. The data cover the period 2010-17 and originate from BISTA and GuV. The main regressor is the double interaction between a Post-dummy equal to one for the third wave of the PHF survey and zero otherwise, and bank-level NCFRs measured in wave 2. In columns (1) and (2), we include all banks in the analysis. Columns (3) and (4) only include regional banks. Data details can be found in Table A1. Time and bank fixed effects are included. Heteroscedasticity-robust standard errors clustered at the bank level are shown in parentheses. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% level.