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Banking Products and Retail Funding: The Effect on Non-Maturing Deposits

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Research Article

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Table of Contents

1. Introduction 4
2. Literature review 5
3. Data 8
4. Identification strategy 11
   Baseline specifications 11
   Difference-in-difference 13
5. Results 17
   Main Results 17
   Robustness 20
6. Discussion and Conclusions 25
   Summary 25
   Implications for managers 25
Declarations 26
References 26
Appendix A 30

Table of Figures

Figure 1. Distribution of the deposited liquidity by product 10
Figure 2. Dynamic effect of each single product (liquidity volumes) 19
Figure 3. Dynamic effect of each single product (liquidity change) 24
Figure 4. Dynamic effect of each single product for each cohort 30

Abstract

Non-maturing deposits are a growing and critical funding source for banks, yet their uncertain cash flows require granular methods to assess depositor behavior and manage liquidity and interest rate risks. Existing approaches rely on aggregate time series, treating all depositors as homogeneous, a key limitation this work addresses.

Using a proprietary dataset of 845,000 retail customers and over 6.5 million annual observations from a large Italian bank (2013–2022), we employ fixed-effects panel regressions, quantile regressions (10th, 50th, 90th percentiles), and a Difference-in-Differences framework with staggered adoption.

Correlational results show banking products increase deposit volumes by 26–94%, while credit products reduce them by 30–59%. Causal DiD estimates are systematically larger, consistent with negative selection attenuation in fixed-effects models. Of six products examined, only three generate statistically significant treatment effects: salary accreditation (+114%), payment cards (+34%), and credit lines (−54%). Personal loans, utility debits, and financial advisory services fail the parallel trends requirement, suggesting their correlational associations reflect customer selection rather than genuine product effects.

These findings establish product composition as a first-order determinant of NMD stability, with direct implications for Asset-Liability Management behavioral models and Basel III liquidity framework runoff rate calibration.

Keywords
Deposit behavior
Difference-in-Differences
Liquidity risk
Non-maturing deposits
Retail banking

1. Introduction

The stability of retail funding has become a central concern for bank management and regulators alike. The bank runs on Silicon Valley Bank and Credit Suisse in 2023 demonstrated that deposit outflows can materialize far more rapidly than traditional behavioral models predict, exposing the limits of aggregate-level approaches to deposit modeling. At the core of this vulnerability lie Non-Maturing Deposits (NMDs) which represent an increasingly significant share of European banks' liabilities. Unlike term deposits, NMDs carry no contractual maturity, allowing customers to freely add or withdraw funds at any time. This optionality makes their cash flows inherently unpredictable and sensitive to behavioral, macroeconomic, and competitive factors, exposing banks simultaneously to liquidity risk and interest rate risk.

Because of this uncertainty, banks rely on behavioral models to estimate the stable portion of NMDs that can fund long-term assets. These models are central to Asset-Liability Management (ALM) decisions, influencing maturity transformation, liquidity buffers, and internal pricing. Regulatory frameworks such as Basel III have further reinforced the importance of robust behavioral assumptions by introducing metrics like the Liquidity Coverage Ratio (LCR) and the Net Stable Funding Ratio (NSFR), and by scrutinizing internal runoff models (Basel Committee on Banking Supervision, 2011, 2013, 2014). Yet most existing models rely on aggregate time series of deposit flows, implicitly assuming that all depositors within a portfolio behave similarly. We argue that this assumption is not only theoretically questionable but empirically unsupported.

The critical gap in the literature is the absence of causal micro-level evidence on how specific banking products shape individual depositor behavior within NMD portfolios. Prior studies suggest that multi-service engagement correlates with higher balances and customer retention (Diepstraten & van der Cruijsen, 2017), and theoretical work on relationship banking predicts that product bundling deepens customer ties (Boot, 2000). However, evidence on the causal impact of individual products, salary accreditation, payment cards, credit lines on deposit volumes and stability remains scarce. Without this evidence, ALM behavioral models cannot distinguish between the stable core attributable to product-driven loyalty and the transient component driven by macroeconomic conditions. Moreover, the rise of multi-banking has increasingly fragmented customer relationships, making product-specific behavioral assumptions more important, and more difficult to estimate from aggregate data alone.

This paper fills this gap by proposing a micro-level approach to NMD modeling, examining how banking, credit, and investment products causally influence the level and stability of individual deposit accounts. Using a proprietary dataset from a major Italian bank, a relevant institutional context given the high dependence of Italian banks on retail funding and the structural characteristics of the domestic household savings market, we track approximately 845,000 customers over the period 2013 to 2022, yielding over 6.5 million annual observations. This granular perspective allows us to link individual product adoption decisions directly to liquidity patterns at the account level.

Our empirical strategy proceeds in two stages. We first estimate the correlational relationship between product usage and deposit volumes using panel fixed-effects and quantile regressions, controlling for individual-level characteristics, relationship variables, and macroeconomic shocks. We then move to causal identification through a Difference-in-Differences framework with staggered treatment adoption, following (Callaway & Sant'Anna, 2021), which addresses the well-known limitations of two-way fixed effects estimators under heterogeneous treatment effects.

Our findings reveal that banking products, particularly salary accreditation, payment cards, and credit lines, have a significant and causal effect on depositor behavior, increasing deposit volumes by 26% to 94% for transactional products while credit lines reduce them by up 30% to 59%[1]. Strikingly, only three out of six products examined exhibit a genuine causal effect when tested against the parallel trends assumption, highlighting the importance of moving beyond correlational evidence in this literature. These results carry direct implications for ALM behavioral models: product composition, not just aggregate deposit flows, should inform the estimation of stable funding horizons and runoff rates.

The remainder of the paper is structured as follows. Section 2 reviews the relevant literature. Section 3 describes the dataset and variables. Section 4 outlines the identification strategy. Section 5 presents the main results and robustness checks. Section 6 concludes with key findings and implications for managers and regulators.

2. Literature review

This paper sits at the intersection of three strands of literature: the modeling of Non-Maturing Deposits, the theory of consumer saving behavior, and the economics of depositor-bank relationships. NMD models tell us how to estimate deposit stability but rely on aggregate assumptions about depositor behavior. Saving theory tells us why individuals accumulate or deplete balances, but rarely at the granularity of individual product adoption. And the relationship banking literature tells us that product bundling deepens customer ties, but stops short of identifying causal effects on deposit volumes at the account level. Our contribution is to bridge all three by providing causal micro-level evidence on how specific product categories shape the level and stability of individual NMD portfolios.

Non-Maturing Deposits carry no contractual maturity and allow customers to withdraw or add funds at any time, exposing banks simultaneously to liquidity risk and interest rate risk through the embedded optionality of the product (Hull, 2018).The foundational contribution to their valuation introduced an arbitrage-free framework for pricing demand deposits, treating the depositor's withdrawal option as a financial derivative (Jarrow & van Deventer, 1998). This was later extended to a more generalized valuation model that accounts for multiple factors affecting NMD pricing and duration, providing banks with a richer toolkit for ALM (Jarrow, van Deventer, & Wang, 2003).

On the risk management side, Kalkbrener & Willing (2004) showed that effectively managing NMDs requires a thorough characterization of both their liquidity and interest rate risk profiles, particularly under volatile market conditions. Maes & Timmermans (2005), analyzing Belgian regulated savings deposits, documented the negative correlation between deposit volumes and market rates Džmuráňová & Teplý (2016) further highlighted that deposit rates do not move mechanically with market rates but are influenced by competitive dynamics, customer expectations, and the availability of investment alternatives a fact that our paper revisits at the individual customer level, showing that this aggregate relationship conceals substantial heterogeneity across product-holding profiles.

A critical limitation shared by all these contributions is their reliance on aggregate deposit flows or portfolio-level data. A partial exception is the recent work of Drechsler, Savov & Schnabl (2021), who show that deposit stability reflects the stickiness of relationship-based depositors, allowing banks to perform maturity transformation without corresponding interest rate risk.

[1] Since the dependent variable is in logarithmic form, all coefficients are converted using the exact formula $(e^{\beta} - 1) \times 100$ to obtain the corresponding percentage change in deposit volumes.

We provide micro-level causal evidence for this mechanism by identifying which products drive depositor loyalty. Rather than estimating a single parameter for NMDs, we recover product-specific effects that enable a more granular behavioral framework.

The urgency of this micro-level approach has been reinforced by recent events. The bank runs on Silicon Valley Bank and Credit Suisse in March 2023 demonstrated that deposit outflows can materialize far more rapidly and at far greater scale than standard behavioral models predict. Post-mortem analyses have highlighted that the composition of the deposit base, not just its aggregate size, was a key determinant of run speed and severity: banks with higher shares of uninsured, non-relationship deposits proved substantially more fragile, with some institutions experiencing outflows of 20–30% per day ((Financial Stability Board, 2024). Jiang, Matvos, Piskorski & Seru (2024) quantified this vulnerability formally, showing that the share of uninsured and non-relationship-based deposits is the single strongest predictor of run exposure among US banks in 2023.

While our data exhibits a clear age-related pattern in deposit holdings, with balances increasing through middle age and declining thereafter, the underlying mechanisms cannot be fully understood within a purely standard framework. The behavioral economics literature has substantially complicated this clean theoretical picture. Hyperbolic discounting leads individuals to under-save relative to their stated long-run preferences due to present-biased time preferences (Laibson, 1997; O'Donoghue & Rabin, 1999). A seminal demonstration that commitment devices and default rules can counteract these biases showed that auto-enrollment in retirement savings programs substantially increases contribution rates (Thaler & Benartzi, 2004). The causal evidence for commitment savings products in a direct banking context comes from (Ashraf, Karlan, & Yin, 2006), who ran a randomized experiment with a Philippine bank and showed that customers offered a dedicated commitment savings account accumulated significantly more savings than the control group. The mechanism is precisely the one we observe for salary accreditation in our setting: channeling funds into an account before the customer can redirect them removes the moment-of-temptation decision and leverages pre-commitment to override present bias.

Financial literacy shapes saving outcomes through a distinct channel: more financially knowledgeable individuals engage in better retirement planning and accumulate greater wealth (Lusardi & Mitchell, 2014; Lusardi, Michaud, & Mitchell, 2017). Evidence specific to Italy shows that financial sophistication is unevenly distributed across the population and is a significant predictor of both product adoption and wealth accumulation, with important implications for the heterogeneity of deposit behavior across customer segments (Lusardi & de Bassa Scheresberg, 2013). In our setting, the presence of a financial advisor, our proxy for investment engagement, serves as a partial instrument for financial sophistication; we document that advised customers exhibit higher total financial assets but lower liquidity in current accounts, suggesting a reallocation toward investment products rather than deposit accumulation. Technological change has further reshaped saving behavior by reducing frictions in account management and product adoption (Gomber, Koch, & Siering, 2017), a development particularly salient in our institutional setting given the bank's predominantly digital platform. The effectiveness of commitment devices in improving saving outcomes has also been demonstrated in field experiments targeting low-income populations, where social network effects further amplify the impact of tailored product design (Karlan, Ratan, & Zinman, 2014; Kast, Meier, & Pomeranz, 2018).

The third strand of literature directly motivates our focus on product bundling as a driver of deposit stability. Early work on relationship banking established that repeated interactions between banks and customers generate private information and switching costs that make the relationship mutually durable (Thakor, 1996; Berlin & Mester, 1999). Cross-country evidence confirmed that firms and by extension

households with longer and more exclusive banking relationships obtain better terms and exhibit greater loyalty (Ongena & Smith, 2000; Degryse & Ongena, 2001). Geographic proximity and soft information also play a role: lenders with access to private information about customers can tailor products more effectively, deepening the relationship (Agarwal & Hauswald, 2010).

Table 1. Overview of Related Literature and Study Contributions

Stream	Key Prior Work	Their Approach & Limitation	This Paper's Contribution
NMD Modeling & Stability	Jarrow & van Deventer (1998); Kalkbrener & Willing (2004); Maes & Timmermans (2005); Džmuráňová & Teplý (2016); Drechsler, Savov & Schnabl (2021); Jiang, Matvos, Piskorski & Seru (2024); FSB (2024); BCBS (2024)	Aggregate deposit flows; uniform behavioral parameters across depositors; no product-level variation; mechanism linking deposit composition to run vulnerability left implicit	Product-level behavioral segmentation; causal micro-estimates of deposit stability by product type; provides the individual-level mechanism assumed in aggregate NMD models and directly relevant for Basel III behavioral model recalibration
Consumer Saving Theory	Laibson (1997); O'Donoghue & Rabin (1999); Thaler & Benartzi (2004); Ashraf, Karlan & Yin (2006); Lusardi & Mitchell (2014); Lusardi & de Bassa Scheresberg (2013); Lusardi, Michaud & Mitchell (2017); Karlan, Ratan & Zinman (2014); Kast, Meier & Pomeranz (2018)	Survey and experimental designs; theoretical models; no product-level bank panel data linking behavioral biases to individual account dynamics	Tests behavioral mechanisms (commitment, inertia, reallocation) on observed product adoption and account-level panel data over 10 years in the Italian retail banking context
Depositor–Bank Relationships	Thakor (1996); Berlin & Mester (1999); Boot (2000); Ongena & Smith (2000); Degryse & Ongena (2001); Agarwal & Hauswald (2010); Iyer & Puri (2012); Diepstraten & van der Cruijsen (2017)	Establishes that product bundling deepens customer ties and reduces run probability; does not isolate the causal effect of individual products from selection of engaged customers into multi-product relationships	Separates the causal effect of individual products from customer selection using a staggered DiD framework; provides account-level evidence for the loyalty mechanism these studies theorize and identifies which specific products drive deposit stability

In the household finance context, Campbell (2006) documented widespread heterogeneity in how individuals manage their financial portfolios, with significant frictions preventing optimal allocation. Bergstresser & Poterba (2004) analyzed asset location decisions within households, while Schleuter, Sievers & Hartmann-Wendels (2014) showed that contractual rewards can stabilize deposits by strengthening the perceived value of the banking relationship. Crucially for our purposes, Iyer & Puri (2012) provided direct evidence that strong depositor-bank relationships reduce the probability of bank runs, with relationship-intensive customers significantly less likely to withdraw during stress events. Their finding — that product engagement proxies relationship depth, which in turn proxies deposit stability — is the theoretical mechanism at the core of our empirical analysis.

Prior studies document that multi-product customers are more loyal on average, but do not isolate the causal effect of individual products from the selection of more engaged customers into multi-product

relationships. Our Callaway & Sant'Anna (2021) Difference-in-Differences framework with staggered treatment adoption addresses this identification challenge explicitly, allowing us to separate the causal effect of product adoption from pre-existing differences in customer behavior.
These studies collectively enhance our understanding of depositor behavior, illustrating the critical interplay between banking practices, depositor information, economic conditions, and the strength of depositor-bank relationships in shaping depositor actions, as summarize in Table 1.

3. Data

The dataset is sourced from the internal database of a large Italian retail bank that, for confidentiality reasons, remains anonymous. The bank is listed on the main Italian stock exchange index and is directly supervised by the European Central Bank as a Significant Institution. As of December 31, 2022 — the end of the observation period — the bank served approximately 1.46 million customers across all 20 Italian regions, with total direct deposits of €30.6 billion and total financial assets under administration exceeding €106 billion. Its business model combines retail banking, investment, and brokerage services through a predominantly digital platform, making it one of the largest retail banking franchises in Italy by number of customers. Italy represents a particularly relevant institutional context for this analysis: Italian households exhibit a high propensity for bank deposit holding relative to other European countries, retail deposits constitute the primary funding source for most domestic banks, and the Italian banking sector is characterized by a high degree of customer loyalty and low switching rates (Vercelli, 2024). While the use of data from a single institution limits direct generalizability, the breadth of the customer base — covering approximately 845,000 retail clients across different age groups, income levels, and geographic areas over ten years — provides sufficient variation to draw conclusions that are informative beyond the specific institution. Moreover, the product set examined — salary accreditation, payment cards, utility debits, personal loans, credit lines, and financial advisory services — is standard across Italian retail banks, further supporting the external relevance of the findings.
The analysis covers the period from January 2013 to December 2022 and is restricted to retail customers, consistent with the bank's predominantly retail funding structure.[1] During the observation period, the bank offered two types of deposit contracts: a floating rate indexed to the 3-month Euribor and a fixed rate set at zero; from January 1, 2018, only zero-rate contracts have been offered.[2] For each contract, we observe key characteristics including contract type, deposit volume, and offered interest rates over its entire lifetime, yielding over 6.5 million annual observations.
The dependent variable is the end-of-month liquidity volume in customer current accounts. The primary variables of interest are binary indicators representing the banking products held by each customer. These include salary credit, indicating whether a customer has chosen to have their income directly deposited into their account; card debits and utility debits, which capture customers' spending patterns; personal loans and credit lines, which detect access to credit; and the presence of a financial advisor, which gauges the customer's inclination towards investment.
In addition to product indicators, we collect a subset of customer characteristics. Age is categorized into five buckets, based on the premise that saving behavior varies with life stages — young individuals typically exhibit different financial preferences and needs compared to middle-aged or elderly individuals, and people tend to reduce savings as they age, leading to a potential decrease in deposit balances over time (Wolff, 2000). Region of residence is grouped into five macro-regions to account for geographical differences in income levels and lifestyle, as individuals in different parts of the country may experience

varying economic conditions (Guiso & Jappelli, 2002; Vercelli, 2024). Finally, we include a continuous risk tolerance index, which is not directly observable and is proxied using a weighted risk rating based on the asset classes held by each client relative to their total financial wealth. Prior studies suggest that higher risk tolerance is associated with lower precautionary savings (Bommier & Le Grand, 2019).

Table 2. Summary statistics

Panel A. Liquidity: Main statistics

Year	N	Mean	p50	Std	Sum
2013	360,213	16,580	4,779	61,217	5,970
2014	404,796	17,357	4,604	56,007	7,030
2015	455,538	19,108	4,609	73,297	8,700
2016	507,539	21,222	4,831	77,266	10,800
2017	565,049	21,059	4,603	75,024	11,900
2018	622,538	21,387	4,461	77,310	13,300
2019	682,295	23,060	4,628	80,471	15,700
2020	730,467	23,985	5,272	81,688	17,500
2021	788,855	23,726	5,195	83,006	18,700
2022	845,741	23,416	4,957	81,534	19,800

Panel B – Mean of main variable by year

Liquidity	Lenght	Wage
16,580	81	3,563
17,357	83	3,571
19,108	85	3,643
21,222	87	3,599
21,059	89	3,602
21,387	92	3,587
23,060	94	3,622
23,985	99	3,704
23,726	102	3,880
23,416	106	4,052

Panel B. Distribution by macro-region

Region	2013	2017	2022
Foreign	0.11	0.44	1.24
North-West	55.4	30.36	31.19
North-East	4.47	10.24	10.1
Center	33.05	36.14	34.81
South	6.96	22.81	22.65
Total	**100**	**100**	**100**

Panel B. Distribution by age classes

Age	2013	2017	2022
<18	0.11	0.19	0.22
18-24	4.47	5.67	6.89
25-44	55.4	47.53	39.53
45-64	33.05	37.95	42.54
>64	6.96	8.64	10.82
Total	**100**	**100**	**100**

Panel C. Mean by product

	Salary		Cards		Utilities		Loan		Cr.Line		Advisor	
Year	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
2013	14,092	19,219	12,344	18,103	14,872	18,491	16,771	6,550	16,914	9,864	18,444	15,751
2014	14,580	20,356	12,006	19,545	15,143	19,946	17,543	7,011	17,661	10,826	19,671	16,391
2015	16,513	22,015	13,161	21,836	17,129	21,356	19,350	7,128	19,455	11,500	20,710	18,459
2016	18,433	24,416	14,834	25,061	19,110	23,487	21,609	8,259	21,614	13,090	22,173	20,801
2017	17,902	24,629	14,901	25,959	18,466	23,690	21,520	8,866	21,466	13,131	21,986	20,619
2018	18,116	25,001	15,511	27,164	18,558	24,103	21,930	9,134	21,827	13,284	21,423	21,369
2019	19,752	26,706	16,938	29,847	20,015	25,852	23,659	10,048	23,510	14,863	22,662	23,271
2020	19,922	28,574	17,580	31,779	20,178	27,412	24,549	11,327	24,411	16,327	23,338	24,337
2021	19,673	28,350	17,461	32,126	19,451	27,503	24,253	12,304	24,153	16,406	22,200	24,552
2022	18,927	28,552	16,961	32,905	18,576	27,657	23,928	12,415	23,816	16,863	20,373	25,117
Mean	**17,791**	**24,782**	**15,170**	**26,432**	**18,150**	**23,950**	**21,511**	**9,304**	**21,483**	**13,615**	**21,298**	**21,067**

Notes: This table presents summary statistics on the main dataset. Panel A presents summary statistics per year of the dependent variable on the whole sample (obs, mean, median, standard deviation and sum) and of the main independent variables (mean). Panel B presents summaries on the frequency by macro-regions and age classes. In Panel C, we present mean values of for each product in case of presence vs absence.

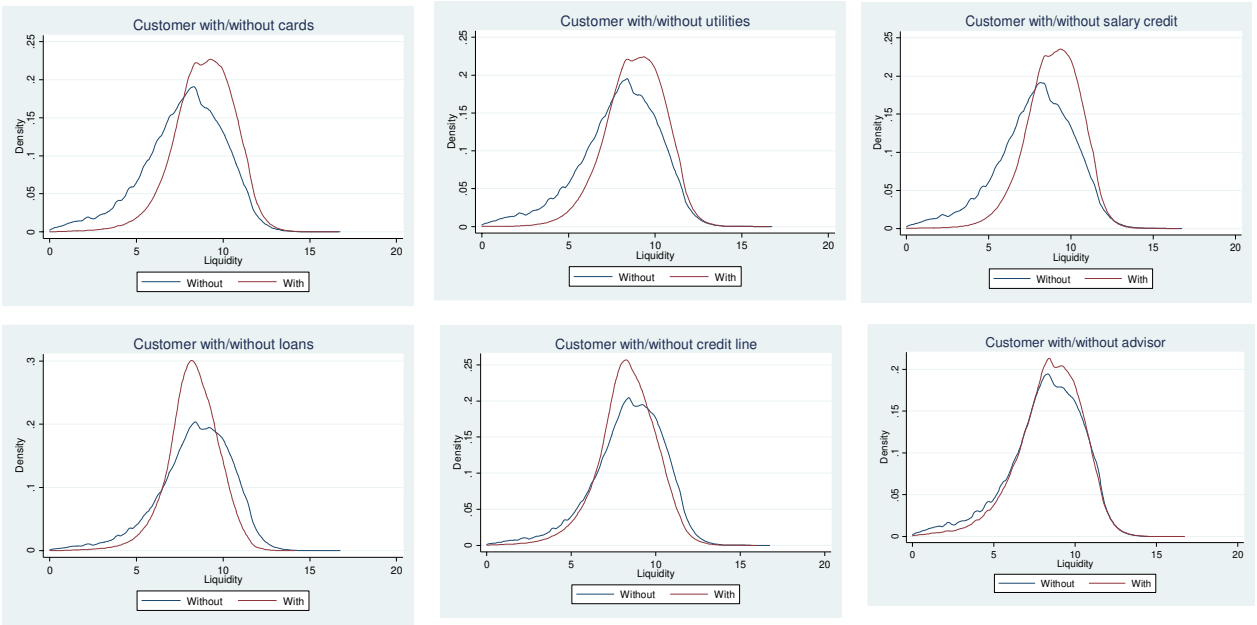
Finally, we include a set of variables describing the bank relationship. These include indicator variables for customer wealth, divided into eight buckets[2], reflecting the idea that saving behavior differs across the wealth distribution, with wealthier individuals generally expected to maintain higher liquidity levels (Fagereng & Natvik, 2021); what we expect is a positive effect of the level of financial assets on the level of liquidity. We also consider the length of the relationship, measured in months since the account was

[2] Following the clustering thresholds of Schlueter et al (2012).

opened, under the assumption that longer relationships imply greater customer loyalty, more products used, and a higher likelihood of increased deposits (Baumann, Burton, & Elliott, 2007). Lastly, we include a measure of volatility, calculated as the logarithmic change in deposited liquidity, based on the premise that customers with lower liquidity volatility are more inclined to maintain stable saving behavior.

When variables are continuous, as in the case of the dependent variable, the annual value is obtained as the mean of the monthly observations. For binary variables, the annual value is derived by averaging the monthly observations and rounding to the nearest integer (0 or 1), thereby indicating usage for the majority of the year, even if the product was deactivated for one or more months.
Table 2 provides an overview of the key statistics related to deposited liquidity, highlighting trends in customer numbers, liquidity amounts, and demographic distributions over a ten-year period.
The distribution of customers across regional clusters and age groups reveals interesting insights over the decade. Although the regional cluster distribution shifts over the years, it remains predominantly concentrated in the North-West and Center regions, which together constitute around 60-70% of the total sample. The age distribution indicates a gradual increase in the 45-64 age group, with a gain of 4-5% compared to the 25-44 group in 2022. This suggests an aging trend within the customer base.
The mean values of key variables—including Liquidity, Wealth, Age, Relationship Length, and Wage—provide additional insights. On average, liquidity constitutes approximately 45% of the total wealth invested in financial products. The increasing average age corroborates the trends observed in the previous data. On the other hand, the growing relationship length reflects increasing customer loyalty. Furthermore, analyzing mean values with and without each product reveals the impact of different product usage on volumes. The mean values for each product per year are presented, showcasing distinct effects. Products like Salary, Cards, Loan, and Credit Line exhibit more pronounced impacts on liquidity volumes. Conversely, the impact on volumes is minimal for Financial Advisor services.

Figure 1. Distribution of the deposited liquidity by product



Note: This figure shows empirical distribution of the logarithm of liquidity of the whole sample. Each graph refers to the distribution of the dependent variable in case of presence/absence of the considered product.

These descriptives provide a comprehensive understanding of the evolving trends in deposited liquidity, customer demographics, and the varying impact of different products on overall volumes.

Some insights regarding the impact of products can be derived from Figure 1 which represents the estimated distribution of the logarithm of liquidity for the contracts with and without different products. The distribution of liquidity for customers using banking products (such as salary deposits, payment cards, and utility debits) shows significantly lower and a shift toward higher overall volumes. In essence, customers who adopt these products tend to hold larger balances, likely due to the nature of these services, which promote regular inflows, transactions, and greater account engagement.

In the context of credit products, the presence of a more left-skewed distribution when the product is in use indicates lower account liquidity. This suggests a few potential scenarios: first, the concentration of lower liquidity values implies that credit products, such as personal loans, might be extended to individuals with relatively lower wealth or available liquidity. Second, in the case of credit lines or overdrafts, customers can access additional funds beyond their current account liquidity. These customers might be leveraging the liquidity provided by the bank to make further investments or manage their financial obligations more effectively.

In contrast, the presence of investment products doesn't appear to have a significant impact on the distribution which remains relatively stable and less affected by skewness[3]. This might indicate that customers using investment products might have more stable or longer-term investment strategies, which could contribute to this observation.

4. Identification strategy

Baseline specifications

The decision to increase account balances may be influenced by a self-selection process driven by unobserved customer characteristics that affect both the choice of specific products and the amount deposited. This creates a potential bias in the model due to endogeneity. For example, depositors who anticipate increasing their balances at a particular bank may choose certain products in advance, knowing that these products align with their future financial behavior. Consequently, this foreknowledge can lead to product selection that skews the model's ability to accurately assess the true effect of the product on deposit amounts.

To address this issue, given the panel structure of our data, we begin by employing a fixed effects model (both individual and time fixed effects). This approach helps to control for unobserved individual characteristics that may be correlated with both the explanatory variables and the dependent variable. By accounting for these time-invariant factors, the fixed effects model reduces potential biases, ensuring a more accurate estimation of the causal relationship between the chosen products and the account balances. This method effectively mitigates the influence of unobserved heterogeneity that could otherwise distort the results (Li & Prabhala, 2007; Roberts & Whited, 2012). This methodology addresses systematic differences among diverse customers by capturing unique, time-invariant characteristics specific to each individual, as well as time-based variations such as seasonal patterns or macroeconomic trends that affect all customers. By controlling for these factors, the model disentangles the complex relationships between product selection, deposit behaviors, and customer attributes. It also helps mitigate

[3] It should be noted that we are assessing the average impact of the financial advisor regardless of the wealth held by the client. We expect this impact to increase as the client's wealth grows. Additionally, it should be considered that the advisor also serves as offline support for account opening, which takes place in the branches of traditional banks. There are clients who may be associated with an advisor solely for assistance in opening an account and who may not be inclined to invest, thereby diluting the advisor's effect on the dependent variable under consideration.

potential sources of bias and endogeneity, providing a clearer understanding of how different products influence account balances, while accounting for external influences like financial market fluctuations or economic cycles:

$$liquidity_{it} = \beta_0 + \beta_1 Wage_{it} + \beta_2 Utilities_{it} + \beta_3 Cards_{it} + B_4 Loans_{it} + B_5 Credit\ Line_{it} + B_6 Advisors_{it} + \delta' X_{it} + \theta' Z_{it} + \alpha_i + \gamma_t + \varepsilon_{it} \quad (1)$$

where the dependent variable is the logarithm of the average yearly liquidity held by a customer in their current account. The independent variables include a set of binary indicators capturing the usage of specific banking services, such as salary crediting, utility bill payments via direct debit, possession of payment cards, activation of personal loans, access to a credit line, and the presence of a relationship with a financial advisor. These variables are intended to measure the marginal impact of each product's usage on the average amount of deposited liquidity, controlling for both observable and unobservable heterogeneity.

The specification also includes two vectors of control variables. The first captures individual customer characteristics and comprises age (grouped into five brackets), macro-region of residence (North-West, North-East, Center, South, and Islands), and a continuous risk tolerance index. The latter is constructed based on the composition of the customer's asset portfolio, ranging from 1 to 6. A value of 1 indicates that the customer holds only risk-free assets, such as current account liquidity, while a value of 6 reflects a high propensity for risk, with a portfolio concentrated in equities or other high-volatility investments. In line with theoretical expectations, we hypothesize a negative relationship between risk tolerance and the level of deposited liquidity.

The second vector includes variables describing the customer's relationship with the bank, specifically the customer's wealth bracket (classified into eight groups[4]), the length of the banking relationship (measured in months since account opening), and the volatility of deposited liquidity, expressed as the annual logarithmic change. The model incorporates individual fixed effects to account for time-invariant unobserved heterogeneity across customers, and time fixed effects to control for common shocks across all individuals in a given year, such as macroeconomic fluctuations or regulatory changes.

The impact of independent variables on the dependent variable can vary significantly depending on the specific quantile of the distribution being analyzed. In our study, the effect of a particular product may differ across various segments of the liquidity distribution. To capture this complexity and strengthen the robustness of our previous models, we have opted to use panel quantile regression. This method allows us to investigate how independent variables influence the dependent variable at different conditional quantiles, such as the 10th, 50th, and 90th percentiles, with a focus on the behavior at extreme percentiles. Panel quantile regression is especially beneficial because it is less sensitive to outliers or data that deviates from a normal distribution. By examining a broader range of conditional quantiles, this approach provides a deeper understanding of the relationships within the data, revealing how product selection and customer behavior affect liquidity across the entire distribution, from the lower to the upper extremes. Furthermore, acknowledging the possibility of temporal dependence in customer account balances—where observations in one period may be correlated with those from previous periods—we estimate a model incorporating an autoregressive AR1 disturbance component.

By simultaneously addressing the complexities of quantile variations and temporal dependencies, our approach provides a comprehensive analysis of the underlying dynamics influencing customer decisions

[4] Following the clustering thresholds of Schlueter et al (2012).

and financial behaviors within the banking context. This rigorous exploration ensures a deeper insight into the factors shaping these behaviors.

Difference-in-difference

The models we have introduced so far provide insights into the effects of using individual products on liquidity. However, they do not establish a causal relationship. In other words, we cannot definitively assert that the use of a particular product directly leads to an increase or decrease in deposited liquidity without accounting for potential confounding factors. Moreover, when individuals choose to use a certain product based on characteristics that are unobservable to the researcher, but correlated with the outcome of interest, estimating causal effects becomes challenging. This makes it more difficult to determine whether the use of the product is actually the cause of the changes in liquidity. (Imbens & Angrist, 1994). Given the panel structure of our data, we have chosen to implement the "Difference-in-Differences" (DID) methodology and more precisely a DID design with multiple periods.

Our scenario involves a staggered treatment adoption, where once a unit is exposed to a treatment, it remains continuously influenced by that treatment. In our context, a customer who begins using a product is classified as a "treated" individual. However, we exclude from our analysis any customers who started using the product but discontinued it during the period under consideration. Consequently, "treated" customers are defined as those who initially did not use the product, began using it, and maintained its use throughout the entire period. This ensures consistency in the treatment group, allowing us to accurately assess the ongoing impact of product usage on liquidity without the confounding effects of treatment discontinuation.

While the Two-Way Fixed Effect (TWFE) model has historically been employed to address such experimental designs, this method isn't suitable for identifying the Average Treatment Effect (ATT) when treatment effects are heterogeneous, and the timing of treatment varies across units. This has been extensively discussed in several works (Sun & Abraham, 2020; de Chaisemartin & D'Haultfœuille, 2020; Borusyak, Jaravel, & Spiess, 2021; Goodman-Bacon, 2021). The core issue with TWFE specifications lies in the inherent nature of OLS regression which tries to exploit all available "variation in treatment status" across different cohorts (groups of units) within the same time window. However, it doesn't distinguish between "treatment" and "comparison" groups[5].

The remedy for this predicament has been proposed by (Callaway & Sant'Anna, 2021), who advocate using all feasible "good" comparisons to estimate ATTs, subsequently aggregating these outcomes to present a consolidated summary of results.

The principal assumption in Difference-in-Differences (DID) designs is the parallel trends assumption. It refers to the idea that the outcomes for both treated and untreated units follow a similar trend over time, prior to the treatment. Specifically, it posits that if the treated units had not received the treatment, their outcomes would have followed the same trajectory as those of the untreated units. While the actual outcomes may differ in levels (for example, one group may have consistently higher or lower outcomes), the rate of change in outcomes over time should be parallel between the groups.

[5] The TWFE model uses these comparisons to estimate the treatment effect, but this can introduce bias because it assumes that the effect of the treatment is homogeneous over time, which might not be true confounding the treatment effect estimation. This comparison adjusts the outcomes of newly treated units based on the outcomes of units already treated which already include the effect of the treatment itself over time. Because of below mentioned reasons, the TWFE combines all into one estimate. This results in a parameter that is difficult to interpret causally. Specifically, the estimate may not reflect a clear treatment effect because it conflates the dynamic effects of treatment (how the effect changes over time) with the initial impact of treatment.

This assumption is consistent with fixed effects models, where the mean of unobserved fixed effects can differ across groups. In other words, each group can have its own unique level of unobserved characteristics, but the effect of time on the untreated potential outcomes should be uniform across all groups. This alignment ensures that any observed divergence in outcomes post-treatment can be attributed to the treatment itself, rather than pre-existing differences in trends.

In the context of staggered treatment adoption, the parallel trends assumption holds that, in the absence of treatment, the average untreated potential outcomes for the group initially treated at time g and the "never treated" group would exhibit parallel trajectories in all post-treatment periods (t≥g).

However, as previously outlined, we refrain from employing the "never treated" as our control group. Consequently, we rely on an alternative version of the parallel trend assumption, specifically tailored to the "not-yet treated" units:

$$E[Y_t(0) - Y_{t-1}(0) \mid X, D_s = 1, G = g] = E[Y_t(0) - Y_{t-1}(0) \mid X, D_s = 0, G \neq g] \quad (2)$$
$$For\ all\ g = 2\ldots, T\ and\ \ s, t = 2, \ldots, T\ \ with\ t \geq g\ \ and\ s \geq t$$

Where,

$Y_{it}(0)$ is unit *i*'s untreated potential outcome. This is the outcome that unit *i* would experience in period *t* if they do not participate in the treatment;

G_i is the time period when unit *i* becomes treated (groups are defined by the time period when a unit becomes treated; hence, the G notation);

D_{is} is an indicator variable for whether unit *i* has been treated by time *t*;

Y_{it} is unit *i*'s observed outcome in time period *t*; for units in the never-treated group we would observed Y_{it}=$Y_{it}(0)$ in all time periods while for units in other groups, we observe $Y_{it} = 1\{G_i > t\}Y_{it}(0) + 1\{G_i \leq t\}Y_{it}(G_i)$. This means we observe untreated potential outcomes for units that have not yet participated in the treatment, and we observe treated potential outcomes for units once they start to participate in the treatment (and these can depend on when they became treated)[6];

X_i is a vector of pre-treatment covariates: in numerous instances, the viability of the parallel trends assumption significantly increases if it remains valid upon considering observed pre-treatment covariates. We employ 1 covariate using the value of wealth[7] in the year the customer starts to use the product.

According to this notion, the "not-yet treated" units at time s $(s \geq t)$ can serve as valid comparison groups when calculating the average treatment effect for the group initially treated at time g. Time s is a time after t during which we observe units that have not yet received the treatment which allows us to use additional data to construct comparison groups.

The comparison is made between the differences in expected untreated outcomes $Y_t(0) - Y_{t-1}(0)$ for the group treated at time g and the differences in expected untreated outcomes for units that have not yet been treated by time s $(with\ s \geq t)$. The left-hand side represents the expected difference in the outcome between time t and $t-1$ for units that will be treated starting in period g, but before they are actually treated (i.e., during the pre-treatment period). The right-hand side represents the expected difference in the outcome between time t and $t-1$ for units that are not treated in period s and belong to different treatment groups (i.e., they are treated in a different period G). In other words, we are comparing the changes in outcomes over time for the treated group with the changes in outcomes for groups that have not yet been treated by the time considered, using the latter as a control group.

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[6] Implicit in this notation there is a no treatment anticipation assumption, which can be relaxed as discussed in Callaway and Sant'Anna (2021), "Difference-in-Differences with Multiple Time Periods".

[7] Calculated as the average of the values over 12 months from the initial sample dataset.

By adhering to these assumptions and employing a suitable control group, we aim to harness the robustness and causal inference capabilities of the DID framework within the context of staggered treatment adoption. This approach is integral to uncovering the impact of banking product activation on customer behaviors, while appropriately accounting for variations over time and potential confounding factors.

In summary, the parallel trends assumption based on not-yet-treated units allows us to use a larger amount of data to construct valid comparison groups but requires pre-treatment trends to be similar between treated and untreated groups, respecting specific temporal conditions between g, s, and t[8].

The above assumptions are natural extensions of the identifying assumptions in the two periods and two groups case to the multiple periods case.

Similarly, a natural progression in generalizing the parameter of interest, also called "Average Treatment Effect on the Treated" (ATT) from the context of two periods and two groups to a scenario involving multiple periods is to establish the concept of group-time average treatment effects:

$$ATT(g,t) = E[Y_t\,(g) - Y_t\,(0) \,|\, G = g] \qquad (3)$$

where,

$Y_{it}(0)$ is unit *i*'s untreated potential outcome. This is the outcome that unit *i* would experience in period *t* if they do not participate in the treatment;

$Y_{it}(g)$ is unit *i*'s potential outcome in time period *t* if they become treated in period g;

G_i is the time period when unit *i* becomes treated.

This represents the average impact of engaging in the treatment for entities within group g during time period t[9].

Under the parallel trends assumptions mentioned above, based on "not-yet-treated units", we have that, for all t≥g:

$$ATT(g,t) = E[Y_t - Y_{g-1} \,|\, G = g] - E[Y_t - Y_{g-1} \,|\, D_t = 0, G \neq g] \qquad (4)$$

Group-time average treatment effects are crucial in Difference-in-Differences analysis with multiple groups and time periods, offering the advantage of capturing variations in effects across groups and time. This flexibility allows for the exploration of heterogeneous effects. However, a drawback is the difficulty in summarizing these effects into a single, concise value.

Among the approaches proposed by the authors, we outline a selection of the most relevant ones to our study, which we will use to present our results. First, we report the average effect of participating in the treatment, separately for each group (where a group is identified by the year of adoption). This is given by:

$$\theta_s(g) = \frac{1}{\mathrm{T} - \mathrm{g} + 1} \sum_{g=2}^{\mathrm{T}} 1\{\mathrm{g} \leq \mathrm{t}\}\mathrm{ATT}(\mathrm{g},\mathrm{t}) \qquad (5)$$

where,

[8] This approach imposes certain restrictions on the pre-treatment trends across different groups, highlighting that there is no flawless solution, and every method comes with trade-offs (Marcus & Sant'Anna, 2021).

[9] It's worth noting that in the case of two time periods and two groups (the standard scenario), the ATT can be expressed as ATT = ATT (g=2, t=2).

$\theta_s(g)$ represents the average treatment effect for group g in year s considering the aggregated treatment effects over different periods;
T is the total number of periods in the dataset;
g indicates the group of interest (in this context, it could be a group that receives the treatment);
$\mathrm{ATT}(g,t)$ is is the Average Treatment Effect on the Treated (ATT) for group g at time t;
$1\{g \leq t\}$ is an indicator function that equals 1 if group g is treated at time t, and 0 otherwise.

This parameter holds intrinsic value as it enables the emphasis on treatment effect heterogeneity concerning the period of treatment adoption. Additionally, the process of further aggregating $\theta_s(g)$ to obtain a comprehensible overarching effect parameter is relatively straightforward.

$$\theta_S^O := \sum_{g=2}^{T} \theta_s(g) P(G = g) \qquad (6)$$

Where,
θ_S^O represents the overall aggregated average treatment effect, taking into account the probabilities associated with each group;
$\theta_s(g)$ is the average treatment effect for group g at a given time period s as defined earlier;
$P(G = g)$ is the probability that an individual belongs to group g;

As estimation method we use the Doubly Robust Inverse Probability Weighting (DR IPW) a regression estimator that uses an inverse probability approach to account for a non-random study design (Seaman & Vansteelandt, 2018; Hernán & Robins, 2020).
The inverse probability approach involves estimating the observation probabilities for each subject in the sample and then using those probabilities to weight the data. This helps to compensate for the fact that some subjects are more or less likely to be observed than others. The DR IPW is a doubly robust and efficient estimator. It is consistent if either the propensity score model or the outcome model is correctly specified, providing an additional layer of protection against model misspecification. Furthermore, the DR IPW tends to be more efficient than using IPW or regression adjustment alone because it leverages information from both models.
The first component of the estimator is the IPW which adjusts for confounding by assigning weights to each observation based on the inverse probability of receiving the treatment that they actually received. The second component is the regression adjustment which models the outcome variable as a function of the treatment and other covariates. A regression model is fitted to predict the outcome based on covariates and treatment status. This helps to adjust for any residual confounding that might not be fully captured by the IPW.
The estimator follows several steps as below reported:
use of a logistic regression to estimate the propensity scores for each individual:

$$\hat{e}(Xi) = P(Ti = 1 \mid Xi) \qquad (7)$$

estimation of the weights for each individual to ensure that individuals in both the treatment and control groups are appropriately weighted:

$$Weight_i = \frac{T_i}{\hat{e}(X_i)} + \frac{1 - T_i}{1 - \hat{e}(X_i)} \qquad (8)$$

fitting of a regression model for the outcome using the treatment and covariates with the following form:

$$Y_i = \beta_0 + \beta_1 T_i + \beta_2 X_i + \epsilon_i \qquad (9)$$

where Y_i is the outcome, T_i is the treatment indicator, and X_i are the covariates;

combination of the estimates from the regression model and the IPW to create a doubly robust estimator by using the regression model to predict the outcome for all individuals and then averaging these predictions using the IPW weights.

5. Results

Main Results

In Table 3 Panel A, we present the outcomes related specification reported at (1). Model 1, incorporating fixed effects, reveals that banking products exert a notably positive and significant influence on volumes. This finding is in line with our anticipated hypothesis, as elaborated in the preceding section.

Table 3. Main results

Panel A1 . Regressions for deposited liquidity in response to banking products (reduced sample)

	TE (1)	TEN (2)	FIFTY (3)	NINTY (4)	AR1 (5)
Banking - Cards = Yes	0.342***	0.405***	0.341***	0.281	0.279***
	(0.008)	(0.069)	(0.096)	(0.231)	(0.006)
Banking - Utilities = Yes	0.322***	0.412***	0.320***	0.234	0.201***
	(0.005)	(0.044)	(0.062)	(0.149)	(0.003)
Banking - Salary = Yes	0.517***	0.664***	0.515***	0.375**	0.292***
	(0.006)	(0.053)	(0.075)	(0.178)	(0.004)
Credit - Loan = Yes	0.070***	0.091	0.070	0.050	0.083***
	(0.008)	(0.083)	(0.117)	(0.279)	(0.007)
Credit - Credit Line = Yes	-0.620***	-0.889***	-0.616***	-0.361	-0.467***
	(0.015)	(0.134)	(0.189)	(0.452)	(0.010)
Investing - Advisor = Yes	0.289***	0.264***	0.290***	0.314	0.195***
	(0.008)	(0.067)	(0.094)	(0.224)	(0.005)
Constant	7.805***				-1.045***
	(0.148)				(0.043)
Observations	1,470,337	1,470,337	1,470,337	1,470,337	1,271,165
Overall R-squared	0.2606				
F-Test	1,730				1,819
Rho AR1					0.519
Number of ids	199,172				184,046

Note: Panel A shows Panel Fixed and Time Fixed effects (TE), Panel Quantile Regressions at 10%, 50%, 90% a Panel fixed effect with AR1 disturbance estimates of our key outcome variables. Positive coefficients are expected for banking and investment products while negative ones are expected for credit producs. Significance is calculated using robust (Huber/White) standard errors clustered by the customer id. We report "Overall R2" for the Panel Fixed and Time Fixed effects results. *, **, *** indicate significance at the 10%, 5%, and 1% level (using a two-sided test), respectively. To deal with high computation time for quantile regressions, we use a random sample 200.000 customers.

Our analyses control for customer-specific and relationship-specific variables, as elaborated upon in the previous section. Furthermore, to account for latent effects stemming from shifts in the global economy, macroeconomic policies, and economic cycles, we incorporate time fixed effects. In Panel A, we only present the main findings regarding the product effect, while the overall applied controls are detailed in the Appendix A.

Table 3 – Main Results

Panel A2 . Regressions for deposited liquidity in response to banking products (full sample)

	TE	AR1
Banking - Cards = Yes	0.342***	0.277***
	(0.004)	(0.003)
Banking - Utilities = Yes	0.322***	0.199***
	(0.002)	(0.002)
Banking - Salary = Yes	0.515***	0.291***
	(0.003)	(0.002)
Credit - Loan = Yes	0.054***	0.070***
	(0.004)	(0.003)
Credit - Credit Line = Yes	-0.634***	-0.475***
	(0.007)	(0.005)
Investing - Advisor = Yes	0.292***	0.192***
	(0.004)	(0.002)
Observations	6,552,074	
Rho AR1		0.517
F-Test	7,780	8,052
Overall R-squared	0.269	
Number of ids	888,578	821,174

Note: Panel A shows Panel Fixed and Time Fixed effects (TE), and Panel fixed effect with AR1 disturbance estimates of our key outcome variables. Positive coefficients are expected for banking and investment products while negative ones are expected for credit producs. Significance is calculated using robust (Huber/White) standard errors clustered by the customer id. We report "Overall R2" for the Panel Fixed and Time Fixed effects results. *, **, *** indicate significance at the 10%, 5%, and 1% level (using a two-sided test), respectively.

Panel B1. Treatment effects (correlation within products)

		Coefficient	Std. err.	t	[95% conf.	interval]	obs	PTA (p-value)
Cards	ATT	0.2893853	0.0490094	5.90	0.1909687	0.3878019	21.565	0.4312
Utilities	ATT	0.0832363	0.0142114	5.86	0.088926	0.1948731	156.759	0.0000
Salary	ATT	0.7629397	0.0213936	35.66	0.7176487	0.8082308	59.643	0.4817
Loan	ATT	0.0301216	0.0294853	1.02	-0.0223986	0.0826418	23.043	0.89056
Credit line	ATT	-0.7818299	0.0451345	-17.32	-0.8667376	0-.6969222	20.813	0.3988
Advisor	ATT	0.0011181	0.0485999	0.02	-0.0896615	0.0918976	16204	0.749

Panel B2. Treatment effects (No correlation within products)

		Coefficient	Std. err.	t	[95% conf.	interval]	obs	PTA (p-value)
Cards	ATT	0.388965	0.1092581	3.56	0.1665653	0.6113647	5406	0.517
Utilities	ATT	0.1418996	0.0262348	5.41	0.088926	0.1948731	52208	0.0014
Salary	ATT	0.953298	0.0336028	28.37	0.8873895	1.019206	30028	0.4943
Loan	ATT	0.0237944	0.0305541	0.78	-0.034919	0.0825077	21836	0.8839
Credit line	ATT	-0.8127409	0.0435995	-18.64	-0.9023731	-0.7231086	19615	0.297
Advisor	ATT	0.0011181	0.0485999	0.02	-0.0896615	0.0918976	16204	0.749

Panel C. Correlation among products

	Cards	Utilities	Salary	Loan	Credit line	Advisor
Cards	1.0000					
Utilities	0.2831	1.0000				
Salary	0.2544	0.3953	1.0000			
Loan	0.0896	0.1207	0.1248	1.0000		
Credit Line	0.1281	0.1454	0.1353	0.1682	1.0000	
Advisor	-0.0389	-0.0198	0.0000	-0.0275	0.0190	1.0000

Note: Panel B estimates treatment effect via the Callway Sant'Anna estimator. In this case, as in the original formulation the authors use Wild Bootstrap to account for heteroscedasticity. For Panel C we use the Pearson's correlation index. This measure ranges from -1 to 1.

By deploying a variety of model specifications, we seek to comprehensively explore the link between product choices and customer behavior, while adjusting for numerous confounding factors. Through

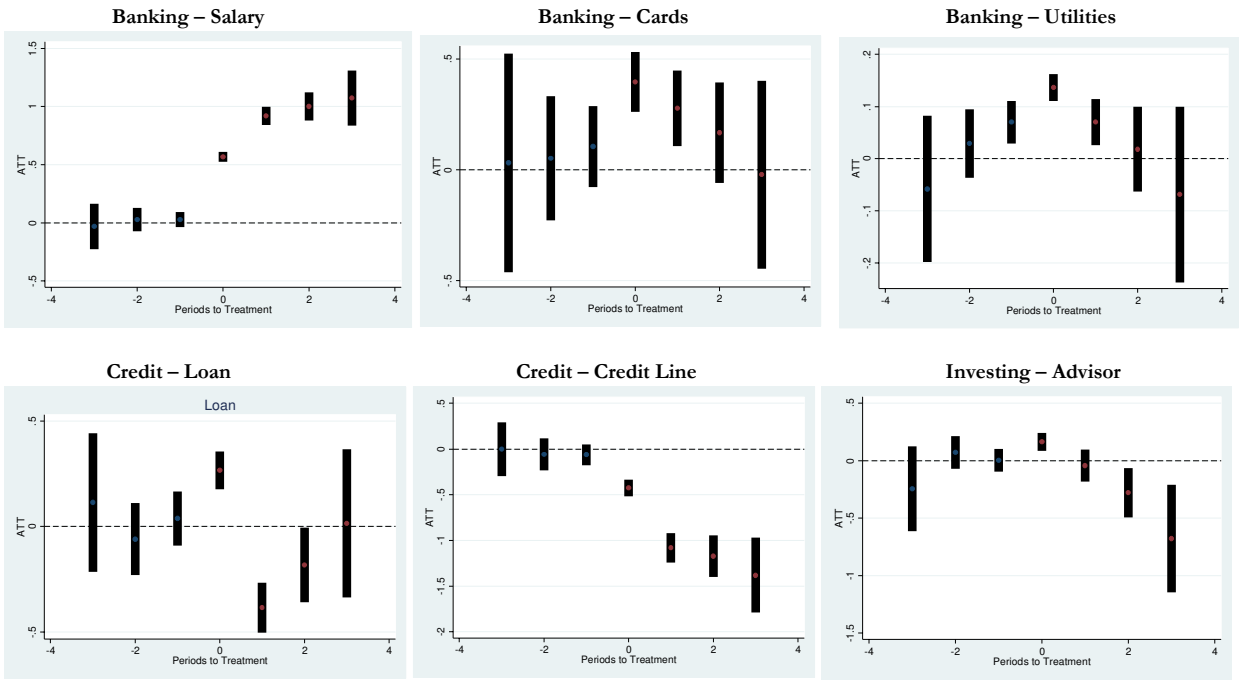
these methodologies, we aim to shed light on the mechanisms underlying saving patterns and to provide a robust foundation for understanding the causal relationships that govern these dynamics.

In Table 3 – Panel B1 we report the ATT as specified in (6). Salary accreditation generates the largest causal effect: a 114% increase in deposit volumes relative to the counterfactual (ATT = 0.763, $p < 0.001$), rising to 159% under the alternative specification. Payment cards generate a causal increase of 34% (ATT = 0.289, $p < 0.001$), though this growth diminishes over time. Cards are likely the first product opened when a new account is created, and in cases where the client does not engage with additional products, their primary banking activity probably remains with another institution, leading to a progressive decline in volumes. Both salary accreditation and payment card effects are persistent over the three-year horizon examined, consistent with transactional product engagement generating structural deposit stickiness rather than a temporary level shift.

Credit lines exert a significant negative causal effect of 54% (ATT = −0.782, $p < 0.001$), suggesting that clients using revolving credit facilities often maintain their primary banking operations elsewhere, treating the credit line as a liquidity buffer that crowds out precautionary deposit holdings. Personal loans show no causal relationship with deposit volumes, further reinforcing this hypothesis.

Personal loans, utility debits, and financial advisory services do not pass the parallel trends requirement. Utility debits, despite showing a positive correlational association, are typically not requested immediately after account opening, and the pre-treatment volume increase suggests they only enhance deposit levels when combined with other products such as salary crediting and cards. For ALM purposes this distinction is critical — including non-causal products in a behavioral segmentation model would overstate the bank's ability to actively influence deposit stability through product policy.

Figure 2. Dynamic effect of each single product (liquidity volumes)



Note: This figure displays the ATT for the not-yet treated in the last 6 years (2017-2022)

For financial advisors, the visual evidence in Figure 3 suggests an initial increase in liquidity volumes, followed by a slight decrease over time. However, this effect is not statistically significant, likely due to the dual role played by financial advisors: acting as a focal point for current account openings but without necessarily leading to invested assets.

This evidence is reported in in Figure 2 where we show the dynamic effect of each product.
To avoid potential confounding effects from other products, a correlation analysis of the various products was conducted, and the results are presented in In Table 3 – Panel C. Specifically, for the banking level, a significant correlation is observed among the three products: 25% between cards and salary deposit, 39% between utilities and salary deposit, and 28% between cards and utilities. For this reason, in the causality analysis for each individual product, products within the same level were excluded (e.g., in the case of salary deposit, we considered only customers treated with that product, excluding those who also use cards and/or utility charges). The results, reported in Table 3 – Panel B2 confirm the evidence of Table 3 – Panel B1 indicating that the correlation between products does not significantly impact the causal effect of each individual product and supporting the robustness of the observed causal relationships for each product independently.
In the Appendix A, we report the graph for each individual product with the dynamic effect for each group separately (year 2017, 2018, 2019...) as reported in (5).

Robustness

Stationarity

To grant greater validity to the obtained results, we conduct a stationarity test on the dependent variable which confirms the series is stationary. We use the Harris–Tzavalis test, which assumes that the number of cross sections tends to infinity while the number of time periods is fixed, to test whether our dependent variable in sample contains a unit root confirming the series is stationary.

Table 4. Stationarity Tests

Harris–Tzavalis	Statistic	z	p-value
rho	0.2226	-42.6652	0.0000

Note: The null hypothesis is that the series contains a unit root, and the alternative is that the series is stationary. To manage computation time, we utilize a random sample of 10,000 customers, each with 10 observations, meeting the requirement for strongly balanced data in the test.

Multicollinearity

Multicollinearity occurs when two or more independent variables in a multiple linear regression model are correlated with each other. To detect multicollinearity, we used the variance inflation factor (VIF) a measure of the correlation between an independent variable and all the other independent variables in the model. A high VIF indicates that the independent variable is highly correlated with the other independent variables[10].
We run an OLS regression and test for multicollinearity, identifying that "Age Cluster" and "Region Cluster" exhibit high VIF values, resulting in an average VIF of 14.01. Eliminating these 2 variables we obtain an average value of VIF equal to 1.91 indicating there is no residual multicollinearity in the model. We report results in Table 5 – Panel A. In panel B we show model (1) with and without Age Cluster and Region Cluster produce similar coefficient.

[10] In models with many independent variables, as in our case, a VIF (Variance Inflation Factor) below 5 is typically considered acceptable, indicating that the variable is not strongly correlated with other independent variables. A VIF between 5 and 10 may suggest moderate multicollinearity but is not necessarily problematic, implying a moderate correlation with other variables. However, a VIF above 10 is generally regarded as a sign of significant multicollinearity, meaning the variable is highly correlated with other independent variables.

Table 5. Multicollinearity tests

Panel A. VIF analysis

Variable	VIF	Variable	VIF
Cards	1.34	Cards	1.32
Utilities	1.3	Utilities	1.29
Salary	1.27	Salary	1.26
Loan	1.06	Loan	1.06
Credit Line	1.09	Credit Line	1.09
Advisor	1.12	Advisor	1.11
Wealth cluster		Wealth cluster	
2	1.21	2	1.21
3	1.36	3	1.35
4	1.29	4	1.29
5	1.24	5	1.24
6	1.21	6	1.2
7	1.65	7	1.62
8	2.27	8	2.18
Age cluster			
2	30.31		
3	138.42		
4	131.85		
5	45.73		
Variable	VIF	Variable	VIF
Region cluster			
1	30.78		
2	14.13		
3	33.33		
4	25.75		
Trading	1.28	Trading	1.28
Lenght	1.38	Lenght	1.26
Volatility	1.09	Volatility	1.09
Risk tolerance	2.86	Risk tolerance	2.86
Year		Year	
2012	1.99	2012	1.99
…		…	
2022	3.53	2022	3.51
Mean VIF	14.01	Mean VIF	1.91

Panel B. Model (1) with/without Region, Age

Variable	MC	No MC
Cards	0.342***	0.347***
Utilities	0.322***	0.332***
Salary	0.515***	0.524***
Loan	0.054***	0.055***
Credit Line	-0.634***	-0.640***
Advisor	0.292***	0.285***

Note: We run a simple OLS with all the variable considered in Model (1). After that we use the command VIF of STATA.

Combined effects

This analytical approach is valuable because there is reason to believe that the relationship between the two variables is not constant but is influenced by the presence of another variable.

The results in Table 6 confirm those reported in Table 3; however, as expected, we observe stronger effects, especially at the banking level. The higher coefficients are due to both the combined impact of various products and the fact that the reference category now consists of customers who do not use any products at a specific level. Specifically, for products at the banking level, this dual effect is even more pronounced because a customer who lacks cards, utility charges, and salary deposits essentially does not use the bank account.

Regarding the credit products, the outcome is similar to that in Table 3, as the effect is primarily driven by the credit line, while the effect of the loan is almost negligible.

Table 6. Main results for deposited liquidity considering interaction effects

VARIABLES	(1) TE	(2) TEN	(3) FIFTY	(4) NINTY	(5) AR1
No.Cards - No.Utilities - Yes.Salary	0.813***	1.003***	0.811***	0.630***	0.493***
No.Cards - Yes.Utilities - No.Salary	0.594***	0.769**	0.592***	0.426**	0.399***
No.Cards - Yes.Utilities - Yes.Salary	1.140***	1.431***	1.136***	0.860***	0.682***
Yes.Cards - No.Utilities - No.Salary	0.597***	0.703**	0.596***	0.495***	0.443***
Yes.Cards - No.Utilities - Yes.Salary	1.099***	1.393***	1.094***	0.815***	0.746***
Yes.Cards - Yes.Utilities - No.Salary	0.928***	1.147***	0.925***	0.717***	0.663***
Yes.Cards - Yes.Utilities - Yes.Salary	1.228***	1.547***	1.224***	0.921***	0.814***
No.Loan - Yes.Credit Line	-0.611***	-0.882**	-0.608***	-0.351	-0.463***
Yes.Loan - No.Credit Line	0.076***	0.097	0.076	0.056	0.088***
Yes.Loan - Yes.Credit Line	-0.541***	-0.782	-0.537*	-0.308	-0.397***
Investing - Advisor	0.284***	0.257	0.284***	0.310***	0.193***
Constant	7.512***				-1.206***
Observations	1,470,980	1,470,980	1,470,980	1,470,980	1,271,828
R-squared	0.2613				
Number of ids	199,152				184,122

Note: Table 5 shows Panel Fixed and Time Fixed effects (TE), Panel Quantile Regressions at 10%, 50%, 90% a Panel fixed effect with AR1 disturbance estimates of our key outcome variables. Positive coefficients are expected for banking and investment products while negative ones are expected for credit products. Significance is calculated using robust (Huber/White) standard errors clustered by the customer id. We report "Overall R2" for the Panel Fixed and Time Fixed effects results. *, **, *** indicate significance at the 10%, 5%, and 1% level (u sing a two-sided test), respectively. To deal with high computation time for quantile regressions, we use a random sample 200.000 customers.

Causality – Timing of choices

To enhance the robustness of obtained causality results, we test if some observable characteristics consistently predicts the timing of the choice of a specific product conditional on the choice itself (Deshpande & Li, 2019).

Table 7 shows the OLS regression results for the period from 2014 to 2022. We run regressions every two years, starting from the last available year, and going back. Note that for the Credit Line product, no results are reported for 2022 due to a lack of available observations.

To examine whether specific characteristics of the customer predict the timing of choice of a product conditional on the choice for each year between 2013–2022, we limit the sample to customer that have no product in that year but will choose it in the future and estimate the following equation:

$$Year\ of\ product\ choiche_i = \beta_0 + \beta_1 Liq_{opendate_i} + \beta_2 Wealth_i + \beta_3 RiskAversion_i + B_4 Volatility_i + \varepsilon_i$$

where,

$Liq_{opendate_i}$ is the liquidity on the account customer i in the year he opened the account,
$Wealth_i$ is the asset wealth of th customer in the previous year,
$RiskAversion_i$ is the Risk tolerance of the customer in the previous year,
$Volatility_i$ is the volatility of the account in the previous year.

The regression results suggest that the timing of a customer's product choice is largely random, even if the choice of the product itself could be not. This conclusion is supported by the low R-squared values across all models, indicating that the observed characteristics do not strongly predict the timing of the product choice.

Table 7. Timing of choiches

Salary	(2) 2016	(3) 2018	(4) 2020	(5) 2022
Wealth (previous year)	0.000	0.000	0.000	0.000
Liq at open date	-0.000	-0.000	-0.000**	-0.000***
Risk tolerance (previous year)	-1.512	-0.405	-0.533	-1.527**
Volatility (previous year)	28.968	5.918	0.096	-2.688
Constant	2,008.986***	2,012.083***	2,021.925***	2,015.902***
Observations	1,582	3,349	4,693	21,888
R-squared	0.002	0.000	0.001	0.001

Cards	(2) 2016	(3) 2018	(4) 2020	(5) 2022
Wealth (previous year)	0.000	0.000	-0.000	0.000
Liq at open date	0.000	0.000	0.000	0.000
Risk tolerance (previous year)	6.063	3.072	3.109	5.638***
Volatility (previous year)	1.481	-228.733***	0.092	-41.675**
Constant	1,979.390***	2,020.544***	2,007.845***	1,990.251***
Observations	581	837	767	5,339
R-squared	0.005	0.030	0.003	0.004

Credit Line	(1) 2014	(2) 2016	(3) 2018	(4) 2020
Wealth (previous year)	0.000	-0.000	0.000	0.000
Liq at open date	-0.000	0.000	0.000	0.000
Risk tolerance (previous year)	3.243**	1.101	0.601	-0.158
Volatility (previous year)	2.876	8.692	-6.598	1.793
Constant	2,000.569***	2,008.746***	2,015.591***	2,021.045***
Observations	4,459	6,941	7,125	5,640
R-squared	0.002	0.000	0.000	0.000

Note: Table 6 shows OLS regression for the whole period (we run the regression every 2 years starting from the last available year and going back).

Treatment effects on liquidity change

We conducted the same Difference-in-Difference analysis in the context of staggered treatment adoption, using the logarithmic change in liquidity volumes as the dependent variable instead of the level. The results are reported in Table 8.

Table 8. Treatment effects on liquidity change

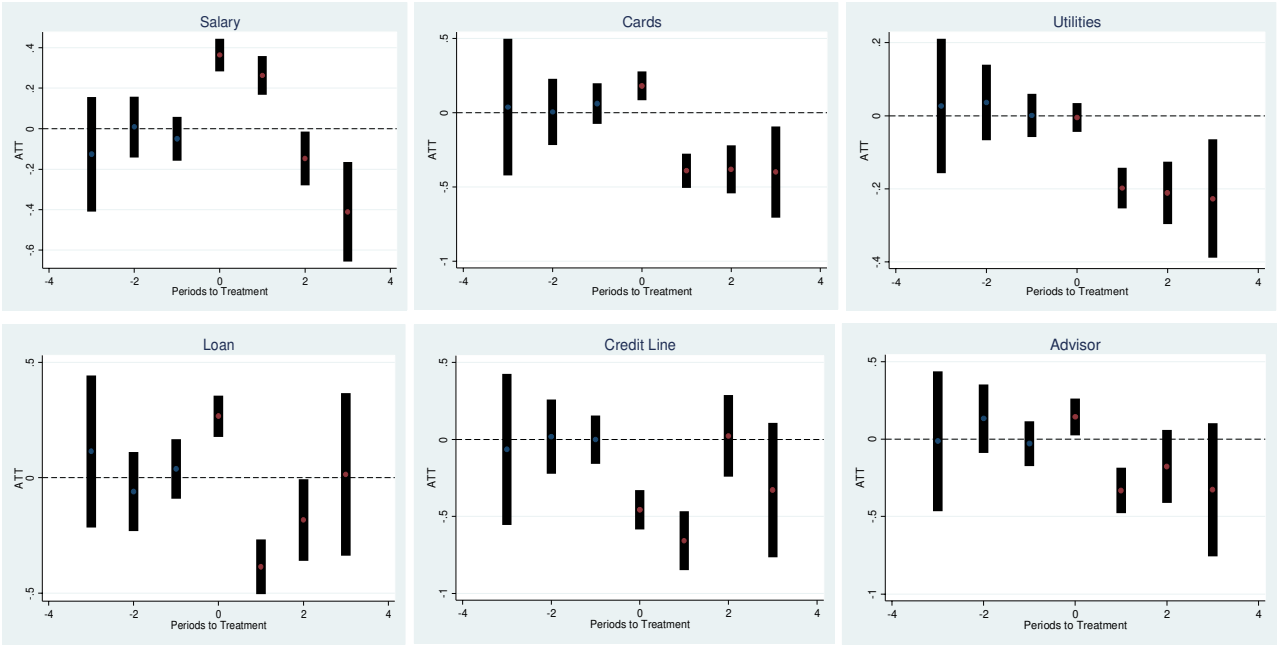
		Coefficient	Std. err.	t	[95% conf.	interval]	obs	PTA (p-value)
Cards	ATT	-.1413352	.0385969	-3.66	-.2186631	-.0640074	22,012	0.2953
Utilities	ATT	-.1048029	.0169969	-6.17	-.1350104	-.0745954	94,422	0.8836
Salary	ATT	.2291737	.0289282	7.92	.1686999	.2896476	39,248	0.1046
Loan	ATT	.0304174	.0322551	0.94	-.0340817	.0949166	21,515	0.89056
Credit line	ATT	-.4336987	.0494669	-8.77	-.5274948	-.3399026	16,569	0.5812
Advisor	ATT	-.060205	.0447943	-1.34	-.1460228	.0256128	16.057	0.4789

Note: This table reports the estimates of treatment effect via the Callway Sant'Anna estimator. In this case, as in the original formulation, the authors use Wild Bootstrap to account for heteroskedasticity.

The study reveals varying effects of different banking products on liquidity changes. Salary deposits show a clear positive impact, indicating that clients who regularly deposit their salary tend to increase their liquidity over time. However, how can be noticed in Figure 3 where we report the dynamic effect of each

product on liquidity change, for salary deposits, although the overall effect remains positive—despite a positive variation at the time of product adoption and in the first year—from the second year onward, the variation becomes negative. This indicates that although volumes increase over time, the variations tend to decrease.

Figure 3. Dynamic effect of each single product (liquidity change)



Note: This figure displays the ATT for the not-yet treated in the last 6 years (2017-2022)

On the other hand, products like payment cards, utility payments, and credit lines are associated with a reduction in liquidity. This suggests that these products lead to more outflows or reduced deposits. Loans and financial advisors show relatively weaker and less significant effects on liquidity, with no strong evidence to suggest they significantly alter liquidity volumes.

For cards and utilities payments, the direction of the effects differs between liquidity change (negative) and liquidity volumes (positive), indicating potential short-term reductions but overall increases in liquidity. Additionally, for utility payments, the Parallel Trend Assumption is satisfied. This may be due to the fact that while total liquidity volumes can vary significantly among customers due to factors such as income, spending habits, or financial preferences—creating greater disparity between treated and untreated groups—logarithmic changes tend to standardize and reduce the scale of differences, making the treated and untreated groups more similar in terms of pre-treatment trends.

6. Discussion and Conclusions

Summary

This study examines how specific banking products causally influence the level and stability of Non-Maturing Deposit portfolios, using a proprietary dataset of approximately 845,000 retail customers observed over ten years (2013–2022) at a large Italian retail bank. A fixed-effects panel regression establishes the correlational relationship between product holding and deposit volumes, controlling for individual characteristics including age, region of residence, and risk tolerance. Quantile regressions at the 10th, 50th, and 90th percentiles confirm that these relationships hold across the full distribution of deposit balances. A Difference-in-Differences framework with staggered treatment adoption, estimated following Callaway & Sant'Anna (2021), then moves from correlation to causal identification. Of the six products examined, three pass the parallel trends validation and generate statistically significant causal effects: salary accreditation, payment cards, and credit lines.

Implications for managers

Salary accreditation should be treated as the highest-priority product for deposit base stabilization. Its causal effect operates through a commitment mechanism: channeling income directly into the account before discretionary spending occurs generates a structurally more stable deposit base. Payment cards reinforce stability through a complementary channel where frequent transactions increase switching costs and operational account dependency making bundling with salary accreditation a natural strategy to compound both effects. Credit lines require separate treatment in ALM models: their negative causal effect on deposits means that portfolios with high credit line penetration should receive lower stability weights, regardless of their aggregate volume. More broadly, our findings support a shift from portfolio-level runoff rates to product-stratified behavioral parameters in NMD modeling.

Implications for policymakers

The bank failures of March 2023 exposed the limits of aggregate behavioral assumptions in internal liquidity models. The Basel Committee on Banking Supervision (2024) has since called for a reassessment of NMD behavioral parameters with particular attention to deposit composition. Our results provide direct empirical support: product-level composition is a first-order determinant of deposit stability, and aggregate parameters mask substantial within-portfolio heterogeneity relevant for stress scenario calibration under the LCR and NSFR frameworks. Supervisors reviewing internal NMD models under IRRBB guidelines should require banks to demonstrate that behavioral parameters reflect the actual product composition of their deposit base.

Limitations and future research. The analysis is conducted on a single institution with a predominantly digital business model, which may limit generalizability to branch-intensive banks.

Future research should replicate the analysis across multiple institutions, and extend the window to the post-2022 rate cycle. A natural extension would exploit variation in product bundling sequences to identify dynamic complementarities between salary accreditation, cards, and credit products in the evolution of deposit balances over time.

Declarations

Compliance with Ethical Standards

The author confirms that this manuscript is original, has not been published previously, and is not under consideration for publication elsewhere. The work has been conducted and presented honestly, without fabrication, falsification, or inappropriate data manipulation. All sources have been properly acknowledged, and relevant literature has been appropriately cited. The author agrees to provide data or supporting materials upon reasonable request, subject to confidentiality constraints.

Conflict of Interest

The author declares that there are no competing financial or non-financial interests that could have influenced the work reported in this paper.

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Appendix A

Figure 4. Dynamic effect of each single product for each cohort

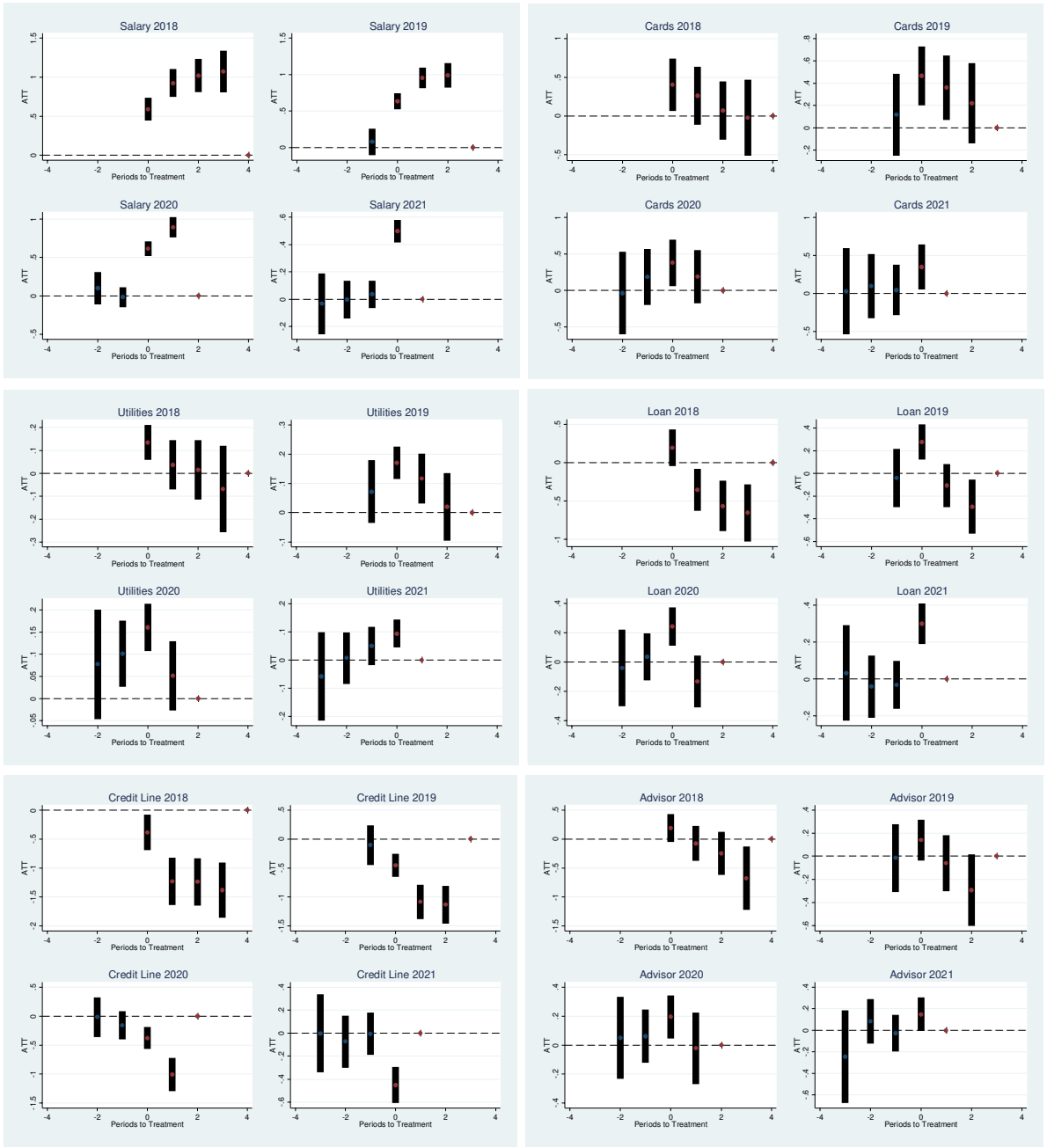


Table 9. Variables description

Variable	Description
Dependent: Logarithm of the average annual liquidity balance	Average annual liquidity balance calculated as the average of 12 monthly observations
Salary	Indicator variable. '1' if contract has accreditation of salary
Cards	Indicator variable. '1' if contract has cards
Utilities	Indicator variable. '1' if contract has debit of utilities
Loan	Indicator variable. '1' if contract has loan
Credit Line	Indicator variable. '1' if contract has credit line
Advisor	Indicator variable. '1' if contract has advisors link
Trading	Indicator variable. '1' if contract has trading operations
Age Cluster	Categorical variable which identifies 5 cluster of age
Wealth Cluster	Categorical variable which identifies 8 cluster of wealth
Region Cluster	Categorical variable which identifies macro-regions of residence (4) or "Foreign"
Vola	Proxy for Risk tolerance. Yearly volatility of the cashflow standardized for the aggregated deposited amount
Length	Length of the relationship (month)

Table 10. Main results for deposited liquidity in response to banking products (overall specification)

VARIABLES	(1) TE	(2) TEN	(3) FIFTY	(4) NINTY	(5) AR1
Banking - Cards = Yes	0.342***	0.405***	0.341***	0.281	0.279***
	(0.008)	(0.069)	(0.096)	(0.231)	(0.006)
Banking - Utilities =Yes	0.322***	0.412***	0.320***	0.234	0.201***
	(0.005)	(0.044)	(0.062)	(0.149)	(0.003)
Banking -Salary = Yes	0.517***	0.664***	0.515***	0.375**	0.292***
	(0.006)	(0.053)	(0.075)	(0.178)	(0.004)
Credit - Loan = Yes	0.070***	0.091	0.070	0.050	0.083***
	(0.008)	(0.083)	(0.117)	(0.279)	(0.007)
Credit - Credit Line = Yes	-0.620***	-0.889***	-0.616***	-0.361	-0.467***
	(0.015)	(0.134)	(0.189)	(0.452)	(0.010)
Investing - Advisor = Yes	0.289***	0.264***	0.290***	0.314	0.195***
	(0.008)	(0.067)	(0.094)	(0.224)	(0.005)
Asset(ref:<5000) = 2, 5,000-10,000	0.555***	0.655***	0.554***	0.459*	0.292***
	(0.007)	(0.076)	(0.107)	(0.255)	(0.005)
Asset(ref:<5000) = 3, 10,000-20,000	0.701***	0.835***	0.699***	0.571**	0.386***
	(0.008)	(0.078)	(0.109)	(0.261)	(0.005)
Asset(ref:<5000) = 4, 20,000-30,000	0.801***	0.951***	0.799***	0.656**	0.426***
	(0.009)	(0.092)	(0.129)	(0.309)	(0.007)
Asset(ref:<5000) = 5, 30,000-40,000	0.862***	1.035***	0.859***	0.694**	0.459***
	(0.011)	(0.104)	(0.146)	(0.349)	(0.007)
Asset(ref:<5000) = 6, 40,000-50,000	0.924***	1.109***	0.922***	0.746*	0.476***
	(0.011)	(0.115)	(0.161)	(0.386)	(0.008)
Asset(ref:<5000) = 7, 50,000-100,000	0.989***	1.202***	0.986***	0.784**	0.499***
	(0.011)	(0.101)	(0.142)	(0.340)	(0.008)
Asset(ref:<5000) = 8, >100,000	1.123***	1.385***	1.119***	0.870**	0.509***
	(0.014)	(0.121)	(0.169)	(0.405)	(0.009)
Age(ref:<18) = 2, 18-24	-0.102	-0.066	-0.102	-0.136	0.210**
	(0.142)	(1.370)	(1.925)	(4.603)	(0.089)
Age(ref:<18) = 3, 25-44	0.186	0.226	0.185	0.147	0.352***
	(0.142)	(1.375)	(1.931)	(4.619)	(0.090)
Age(ref:<18) = 4, 45-64	0.188	0.212	0.188	0.165	0.371***
	(0.142)	(1.376)	(1.934)	(4.625)	(0.090)
Age(ref:<18) = 5, >64	0.060	0.108	0.059	0.013	0.339***
	(0.143)	(1.382)	(1.942)	(4.644)	(0.090)
Region (ref:Foreign) = 1	0.138***	0.219	0.137	0.059	0.116***
	(0.043)	(0.363)	(0.510)	(1.220)	(0.026)
Region (ref:Foreign) = 2	0.112**	0.190	0.111	0.037	0.057*
	(0.049)	(0.415)	(0.583)	(1.394)	(0.030)
Region (ref:Foreign) = 3	0.052	0.123	0.051	-0.018	0.056**
	(0.043)	(0.364)	(0.511)	(1.223)	(0.026)
Region (ref:Foreign) = 4	0.025	0.090	0.024	-0.037	0.056**

	(0.044)	(0.378)	(0.531)	(1.269)	(0.027)
Trading = Yes	0.239***	0.267***	0.238***	0.212	0.113***
	(0.005)	(0.057)	(0.081)	(0.193)	(0.004)
Lenght	0.000	0.000	0.000	-0.000	-0.000
	(0.000)	(0.004)	(0.006)	(0.015)	(0.000)
Volatility	-1.788***	-3.487***	-1.764***	-0.151	-0.796***
	(0.028)	(0.309)	(0.435)	(1.040)	(0.018)
Risk Tolerance	-0.298***	-0.320***	-0.298***	-0.278***	-0.209***
	(0.002)	(0.022)	(0.031)	(0.075)	(0.001)
Year = 2012	-0.085***	0.009	-0.086	-0.176	4.175***
	(0.007)	(0.098)	(0.138)	(0.330)	(0.063)
Year = 2013	-0.048***	0.117	-0.050	-0.207	6.404***
	(0.012)	(0.132)	(0.185)	(0.443)	(0.096)
Year = 2014	-0.024	0.192	-0.027	-0.232	7.574***
	(0.017)	(0.175)	(0.246)	(0.588)	(0.113)
Year = 2015	0.040*	0.297	0.036	-0.209	8.227***
	(0.023)	(0.222)	(0.312)	(0.746)	(0.123)
Year = 2016	0.074***	0.344	0.071	-0.186	8.569***
	(0.028)	(0.271)	(0.381)	(0.911)	(0.129)
Year = 2017	0.137***	0.419	0.133	-0.135	8.796***
	(0.033)	(0.321)	(0.452)	(1.080)	(0.132)
Year = 2018	0.146***	0.445	0.142	-0.143	8.896***
	(0.039)	(0.372)	(0.523)	(1.250)	(0.135)
Year = 2019	0.170***	0.450	0.166	-0.100	8.976***
	(0.044)	(0.422)	(0.593)	(1.418)	(0.137)
Year = 2020	0.271***	0.540	0.268	0.012	9.098***
	(0.050)	(0.473)	(0.665)	(1.590)	(0.139)
Year = 2021	0.342***	0.525	0.339	0.165	9.191***
	(0.055)	(0.525)	(0.737)	(1.763)	(0.140)
Year = 2022	0.300***	0.294	0.300	0.306	9.166***
	(0.060)	(0.577)	(0.810)	(1.937)	(0.142)
Constant	7.610***				-1.173***
	(0.148)				(0.043)
Observations	1,470,337	1,470,337	1,470,337	1,470,337	1,271,165
Overall R-squared	0.2606				
F-Test	1730.45				1819.27
Rho AR1					0.519
Number of ids	199,172				184,046