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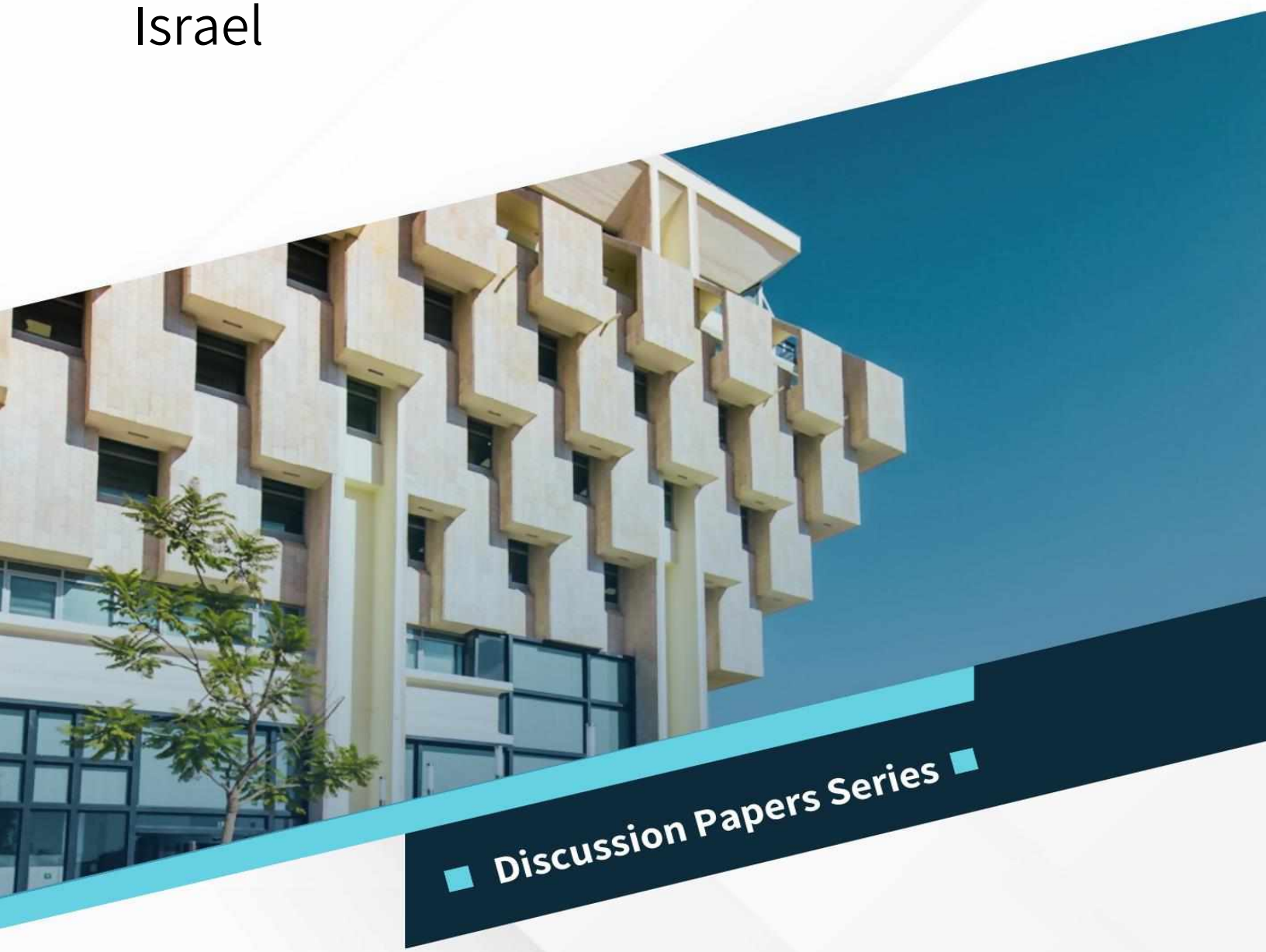
Monetary Tightening and the Role of Nonbank Lenders: Evidence from Israel



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Monetary Tightening and the Role of Nonbank Lenders: Evidence from Israel*

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Abstract

This paper examines how monetary policy affects credit supply from banks versus nonbank financial institutions (NBFIs) using microdata from Israel's Consumer Credit Register from 2021–23. We address identification challenges by employing monetary policy surprises and borrower-month fixed effects following Khwaja and Mian (2008), focusing on borrowers who simultaneously obtain credit from both banks and NBFIs. Our results show that monetary policy tightening leads to a significant shift in market share from banks to NBFIs in consumer credit markets. We identify the funding structure channel as a primary mechanism: following monetary tightening, NBFIs increase their reliance on long-term financing while banks do not. Using proprietary data on inter-institutional lending, we provide direct evidence that banks increase their lending to NBFIs following monetary tightening, which NBFIs then deploy to expand consumer credit.

JEL classifications: E52, E51, G21, G23.

Keywords: Monetary Policy; Banks; Nonbank Financial Institutions; Consumer Credit; Local Projection

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הידוק מוניטרי ותפקידם של מלווים חוץ-בנקאיים: עדות מישראל

נועם מיכלסון[1], טניה סוחוי[2]

תקציר

נייר זה בוחן את השפעת המדיניות המוניטרית על היצע האשראי מבנקים לעומת מוסדות פיננסיים לא-בנקאיים, תוך שימוש בנתונים ממאגר האשראי הקמעונאי של ישראל עבור השנים 2021-2023. לצורך הזיהוי, אנו משתמשים בהפתעות במדיניות המוניטרית ובאפקטים קבועים של לווה-חודש, ומתמקדים בלווים המקבלים אשראי בו-זמנית משני סוגי המוסדות. התוצאות מראות כי הידוק מוניטרי מוביל לגידול משמעותי בנתח השוק של מוסדות פיננסיים שאינם בנקים בשוק האשראי הצרכני. אנו מזהים את מבנה המימון כמנגנון המרכזי: בעקבות הידוק מוניטרי, מוסדות אלה מגדילים את הסתמכותם על מימון לטווח ארוך – בעוד שהבנקים אינם עושים כן – מה שמאפשר להם להרחיב את פעילותם. יתר על כן, אנו מראים כי מקור המימון ארוך הטווח הם הבנקים עצמם, הממלאים תפקיד מפתח בהרחבת האשראי הצרכני של המוסדות הפיננסיים שאינם בנקים.

מילות מפתח: מדיניות מוניטרית; בנקים; מוסדות פיננסיים חוץ-בנקאיים; אשראי צרכני; השלכה מקומית.

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1. Introduction

Models of monetary policy transmission traditionally focus on the effects on bank credit, with the well-established finding that banks reduce their credit supply following monetary tightening. With the increasing share of nonbank financial institutions (NBFIs) in credit markets, questions arise regarding how these entities respond to monetary policy and what implications this has for overall credit volumes in the economy. The answers to these questions have important implications for monetary policy management. If there were no differences in the behavior of different credit providers, changes in the composition of credit sources would have no substantive meaning for how monetary policy is conducted. However, if there are behavioral differences between credit providers, monetary policy must also take into account the composition of credit sources in the economy.

The growing importance of NBFIs in credit markets has prompted a growing body of research that documents the dissimilar relationship between monetary policy and credit supply conditional on the type of financial entity. Chen, Ren and Zha (2018) and Xiao (2020) find that while bank credit decreases following monetary tightening, credit from nonbanks in fact increases. Similarly, Elliott, Meisenzahl, Peydro and Turner (2022) find that higher policy rates shift credit supply from banks to nonbanks in the United States, neutralizing associated consumption effects via consumer loans while attenuating firm investment and house price spillovers. Banarjee and Serena (2022), using a database of syndicated loans, also find that nonbanks indeed substitute for banks, weakening the effects of monetary policy. Cucic and Gorea (2024) show that this effect is evident in both business and consumer credit.

The literature cited heretofore also presents several mechanisms potentially elucidating the differential impact of monetary tightening on credit provision from banks versus nonbank financial institutions. One significant explanatory framework centers on the fundamental divergence in funding structures between these two institutional categories. Banking entities demonstrate substantially greater dependence on short-term public deposits, whereas nonbank institutions tend to rely comparatively more on longer-duration funding sources, with public deposits conspicuously absent from their financing portfolio. Following monetary tightening, there typically occurs a withdrawal of short-term deposits from banks, consequently constraining their credit-extending capabilities, while nonbanking institutions do not experience a comparable phenomenon. Although a portion of these deposits remains within the banking system in the form of interest-bearing deposits with extended maturities, nevertheless there is a significant capital flow toward money market funds offering better yields, particularly from yield-sensitive, more sophisticated, investors (Xiao, 2020). Cucic and Gorea (2024) empirically demonstrate that subsequent to monetary tightening, long-term funds are redirected into nonbank financial institutions, which subsequently deploy these resources for lending activities to both commercial enterprises and household borrowers. This redistribution of capital flows represents a crucial transmission mechanism through which monetary policy differentially affects various segments of the financial intermediation landscape.

Chen, Ren and Zha (2018) suggest that constraints on the loan-to-deposit ratio in banks increase due to the risk of deposit outflows, and to mitigate this, banks provide less credit and invest more in other assets, including off-balance-sheet assets that enable

nonbanks to provide credit. Drechsler, Savov and Schnabl (2022) documents that during the 2003–06 period when the Federal Reserve raised interest rates, deposits flowed out of banks to nonbank credit companies, which then expanded mortgage lending. Agarwal, Hu, Roman and Zheng (2023) point at another—though, related—channel, which is the mortgage servicing channel. While banks are heavily affected by interest rate hikes, nonbanks that hold mortgage-servicing rights receive continue to receive fixed monthly income and expect lower rates of refinancing. This, in turn, allows nonbanks to continue providing credit.

In addition to the different funding structure of banks and NBFIs, Banarjee and Serena (2022) identify two more structural reasons why the impact of monetary policy on nonbank loans might differ from its impact on bank loans. The first is the lower leverage of nonbanks relative to banks. Jiang, Matvos, Piskorski and Seru (2023) also document lower leverage of NBFIs on average, but higher variance than in banks.[1] Second, nonbanks' monitoring methods focus primarily on preloan assessment, making them less sensitive to decreases in borrower value following interest rate increases.

Concurrent with this corpus of research, a significant body of literature has emerged in recent years examining the direct interrelationship between banks and NBFIs. Jiang (2023) has elucidated the centrality of banks in NBFI financing, while simultaneously highlighting how banks compete with these same NBFIs in specific market segments. Banking institutions strategically leverage the dependency of NBFIs on them for financing requirements to mitigate competition in those market segments where they contend, exemplified by mortgage lending activities. Acharya, Cetorelli, and Tuckman (2024) have conducted a comprehensive empirical analysis of the multifaceted interconnections between banks and nonbanks, identifying a significant bidirectional dependency between these institutions, with particular emphasis on nonbanks' reliance on bank-provided financing. The credit and liquidity risks ostensibly transferred from banks to nonbanks have not been eliminated but rather transformed, with banks continuing to face substantial risks associated with nonbank activities and exposures. This intensifying interconnectedness manifests in an increasingly robust correlation between the yield performances of these two institutional categories, necessitating regulatory reconsideration regarding the potential merit of adopting a more holistic regulatory framework, encompassing both institutional types (Acharya, Gopal, Jager, and Steffen, 2024). In a related investigation, Krainer, Vaghefi, and Wang (2024) discovered that banks demonstrate a propensity to augment financing to nonbanks following shocks to their regulatory capital, suggesting that regulatory capital requirements likely exert a significant influence on the magnitude of credit extended by banks to nonbank financial institutions. This finding underscores the complex regulatory arbitrage dynamics that may characterize the bank/nonbank nexus within the contemporary financial ecosystem.

This paper utilizes consumer credit register microdata to bridge the aforementioned themes and demonstrate the differential response in the consumer credit market, from nonbank financial institutions to monetary policy interventions. It identifies the funding structure channel as an explanatory mechanism for this phenomenon and quantifies the

[1] Jiang, Matvos, Piskorski and Seru (2023) claim that NBFIs are essentially banks without access to deposits. Additional findings are that NBFIs primarily borrow from more sophisticated lenders, that their leverage increases with size, with the largest resembling similar-sized banks. The share of uninsured liabilities in NBFIs grows with their size, and the interest on this debt decreases with size.

contribution of banks as financiers of nonbank institutions in explicating it. To establish causality, two significant identification challenges must be addressed. The first stems from monetary policy being contingent upon other macroeconomic developments that potentially impact on both credit supply and demand dynamics. The second arises from the heterogeneous composition of borrower portfolios between banks and nonbanks, whereby certain macroeconomic and monetary policy developments may differentially affect each borrower category. We overcome the first challenge by employing monetary policy surprises rather than central bank interest rates as our metric for monetary policy. Since monetary surprises are, by definition, unanticipated ex ante and therefore independent of other macroeconomic developments, the estimated effect can be attributed to monetary policy rather than confounding factors.

To address the second challenge, we implement the methodological approach developed by Khwaja and Mian (2008), as similarly applied by Cucic and Gorea (2024). Through the utilization of monthly data from Israel's official credit registry, we identify a subset of borrowers who simultaneously obtain credit from both banks and nonbank institutions, and incorporate borrower-month fixed effects. This methodology neutralizes potential observable and unobservable impacts of economic conditions and monetary policy on credit demand, thereby enabling the attribution of any changes occurring in response to monetary surprises exclusively to the credit supply dimension of various financial institutions. Using this setting, we examine the dynamic impact of monetary policy on the relative market share of nonbanks versus banks. While Cucic and Gorea (2024) utilized annual data, our application of monthly data enables more precise identification of the temporal dynamics of this impact. Our results corroborate previous findings in the literature: following monetary policy tightening, the market share of non-bank institutions expands at the expense of traditional banks in the consumer credit market. We find no support for the hypothesis that this compositional shift results from alterations in risk preferences through a risk-taking channel of nonbanks.

Subsequently, we examine the underlying mechanism driving the compositional shift. Based on literature proposing divergent funding structures as a potential explanation, we utilize data concerning the funding structure of both banks and nonbanks, with particular emphasis on their relative dependence on long-term versus short-term debt. We discover that following monetary tightening, the proportion of long-term financing increases among nonbank institutions, subsequently cascading into the consumer credit market. Finally, leveraging unique microdata, we assess the extent to which the financial interconnection between banks and nonbanks contributes to explaining this phenomenon. We find direct evidence that following monetary tightening, banks increase their lending to nonbank financial institutions, which in turn deploy these funds to expand their market share in the consumer credit sector. This finding elucidates an important transmission channel through which monetary policy tightening affects financial intermediation and credit allocation in the broader economy.

The remainder of this paper is organized as follows: Section 2 provides a brief overview of data we use in this paper; Section 3 sketches the methodology we use in paper; Section 4 includes descriptive statistics of the data we use; Section 5 encompasses the empirical analysis; and finally, Section 6 discusses the results and concludes the paper.

2. Data

In this study, we utilize administrative data from the Israeli Consumer Credit Register (hereafter: "the Register"), which encompasses all consumer credit information for the entire population of borrowers in Israel.[2] Established in 2016 under the "Credit Data Law," the Register aims to boost competition in the retail credit market by facilitating the sharing of credit information. Managed by the Bank of Israel, it mandates that all banks and credit card companies report their new and existing credit data monthly. Only financial institutions that share their borrower data can use the database.

The Register includes comprehensive monthly information on the current balance in each of the consumer credit facilities: consumer loans (including auto loans), credit through credit cards, credit lines, overdrafts, and mortgages. In addition to the current balance, lenders also report the contractual interest rate at the time of loan origination, collateral information, and amounts of credit for which there are payment delinquencies. Each credit transaction contains unique identifiers for both the borrower and the lender, enabling the observation of all transactions conducted by a specific borrower with each credit provider reporting to the database. The socioeconomic characteristics of borrowers are relatively limited, encompassing the borrower's age cohort and residential locality, to which we append the socioeconomic status of the locality based on data from the Central Bureau of Statistics. Additionally, the Register includes an indicator specifying whether the borrower obtained the loan for microbusiness purposes managed by the borrower or for household consumption.

From the Register, we select only unsecured credit transactions and exclude auto loans and mortgages. Although auto loans comprise the majority of consumer credit, we exclude them because during the sample period, a significant and exogenous structural transformation occurred in this market segment. This change was partially attributable to the implementation of the Register, but predominantly resulted from a strategic business decision by banking institutions to systematically withdraw from this market. This withdrawal followed prudential guidelines issued by the Supervisor of Banks in 2017, which, while not legally binding, strongly encouraged commercial banks to restrict their exposure to auto loans with loan-to-value ratios exceeding 60 percent. Such structural shifts could potentially generate spurious correlations between interest rate trajectories or monetary policy surprises and the expanding market share of nonbank financial institutions in household credit extension, necessitating the exclusion of these transactions from our analytical framework. Nevertheless, it is noteworthy that in practice, all results in this paper remain substantively identical whether auto loans are included or excluded from the analysis. We omit mortgages because nonbank entities in Israel have minimal participation in the mortgage market, which is dominated entirely by commercial banks.

The lending institution is explicitly identified and categorized into one of two groups: banks and nonbanks. The latter group is made up of three types of financial institutions: credit card companies, nonbank credit companies, and institutional investors providing credit to households. We exclude the latter from our sample since loans provided by

[2] The Register has also been used by Bank, Segev and Shaton (2023) and Caspi, Eshel and Segev (2024).

insurance companies and institutional entities are fundamentally different and are only given to customers who have long-term savings with the same company, and the interest rate they charge must not exceed a certain regulatory threshold set by their regulator.

The majority of credit extended in Israel is provided by publicly traded companies. This enables us to extract from financial statements all balance sheet items relevant to the analysis of the funding channel, including total assets, total equity, total liabilities, and their distribution between current liabilities (up to one year) and long-term liabilities. However, financial statements do not consistently detail the proportion of liabilities attributable to bank financing versus other sources. For this purpose, we utilize a proprietary database of all major borrowers in the banking system as reported by commercial banks to the Bank of Israel. This reporting occurs quarterly and includes all credit exposures exceeding NIS 50 million at each bank, with details regarding the client and the type of exposure (on-balance sheet credit or off-balance sheet credit such as credit lines). Through this database, we identify the amount and type of credit supplied by banks to those nonbank companies identified as lenders in the Register.

Last, we gather all necessary macroeconomic data for this paper from the Bank of Israel's data warehouse.

3. Methodology

In this section, we outline the models we intend to estimate. Detailed information about the population under study, precise definitions of each variable, and other estimation-related considerations will be provided in the results section.

3.1. Transmission of monetary policy through NBFIs

To examine whether monetary policy affects bank credit and credit from NBFIs differently we would have wanted to estimate the following equation:

$$(1)\ \log(consumer\ debt)_{l,t} = \alpha + \beta_1 is\_non\_bank_l + \beta_2 \times monetary\_policy_{t-m} + \beta_3 is\_non\_bank_{l,t} \times monetary\_policy_{t-m} + \varepsilon_{l,t}$$

Where $\log(consumer\ debt)_{l,t}$ is the log of total credit balance of institution l at time t, $is\_non\_bank_l$ is an time invariant indicator that takes the value 1 if l is an NBFI, and $monetary\_policy_{t-m}$ is the policy interest rate at time t-m that measures the monetary policy at time t-m. However, estimating this equation will result in biased results because of two main identification challenges. The first is the close relationship between monetary policy and other macroeconomic conditions that also shape credit in the economy. Given this natural relationship, it is difficult to identify the impact of monetary policy itself on credit supply. The second challenge is the ability to separate the effects of demand from supply, as monetary policy affects both.

We address these identification challenges as follows. Instead of using monetary policy itself, we use the series of monetary policy surprises as calculated by Kutai (2023). To

the extent that these shocks are unexpected, we can examine how they affect credit supply. As for separating demand and supply, we use the framework suggested by Khwaja and Mian (2008): we identify borrowers that borrow from both credit sources—banks and NBFIs—and examine how the loan balance from each source changed after monetary policy surprises, using a fixed effect for borrower-month. This framework effectively isolates all effects related to the borrower, including observed and unobserved variables that might impact on demand, so that the estimated effect is entirely attributed to the effects of credit supply. An illustration of our sample can be found in Table 1. The borrower in this illustration has at time *t* a credit facility with positive balance at institution A which is a nonbank, and another credit facility at institution B, which is a bank. *m* periods (months) before time *t*, there was no monetary policy surprise. At time *t+1*, Borrower 1 had one more credit facility with a positive balance from a institution C, a nonbank, following a monetary policy surprise at time *t+1-m*.[3]

Table 1. Illustration of the structure of the data

	Period	Is lending institution a nonbank	Total balance	Monetary policy shock *m* periods ago
Institution A	t	1	100K	0
Institution B	t	0	50K	0
Institution C	t	1	0	0
Institution A	t+1	1	90K	0.1
Institution B	t+1	0	40K	0.1
Institution C	t+1	1	50K	0.1

Formally, we estimate the following equation:

$$(2)\ \log(consumer\ debt)_{i,l,t} = \alpha_{i,t} + \beta_1 is\_non\_bank_l \times monetary\_policy\_surprise_{t-m} + \delta macro\_controls_t \times is\_non\_bank_l + \lambda_l + \varepsilon_{i,t}$$

where the main change compared to a equation (1) is the use of log(debt) at the individual level, the inclusion of $\alpha_{i,t}$, a fixed effect for each borrower and month, and the use of monetary policy surprises at time *t-m* instead of a variable reflecting the policy itself. To control for other macroeconomic developments we include the monthly composite index that measures the current real growth, the local VIX and inflation expectations, interacted with the NBFI dummy variable. We also include λ_l, a fixed effect for the lender.[4] The coefficient of interest is β_2, where a positive value indicates that following a monetary policy there is a shift in the consumer credit share of NBFIs.

We then examine whether the change in credit sources reflects different risk preferences and whether the change occurs through a risk-taking mechanism of NBFIs. For the same population of borrowers who borrow from two different sources, we modify

[3] Changes in credit balance might also stem from changes in credit balance to prior lenders through the same or another credit facility.

[4] Since we use fixed effects for borrower-month and lender, all variables terms without interactions are dropped from the estimation.

equation (2) and add a variable that reflects borrower risk and an interaction with lender identity and monetary shocks as follows:

$$(2A)\ \log(consumer\ debt)_{i,t} = \alpha_{i,t} + \beta_1 is\_non\_bank_l \times monetary\_policy\_surprise_{t-m} + \beta_2 is\_non\_bank_l \times monetary\_policy\_surprise_{t-m} \times borrower\_risk_{i,t} + \delta macro\_controls_t \times is\_non\_bank_l + \lambda_l + \varepsilon_{i,t}$$

If, following monetary shocks, NBFIs increase credit while taking increased risks, we would expect β_2, the coefficient of the triple interaction we added, to be positive.[5]

3.2. Mechanism

To examine whether the different funding structure of banks and NBFIs and banks is what underlies the change in credit sources after monetary tightening, we first examine which funding component is affected by monetary tightening in banks and in NBFIs. As in Cucic and Gorea (2024), we examine this using a regression where the dependent variable is one of the three main funding components of a financial institution: short-term liabilities, long-term liabilities, and equity. We also add a fourth, synthetic, component which represent all non-short-liabilities, and calculated by the sum of equity and long-term liabilities. Formally, we estimate:

$$(3)\ \Delta funding_{l,t} = \alpha_l + \beta_1 monetary\_policy\_surprise_{t-m} + \delta macro\_controls_t + \varepsilon_{l,t}$$

where the dependent variable is the log difference in one of the four funding components we defined in institution *l*, and the explanatory variables are a monetary policy surprise at time *t-m* shock, alongside macro variables and a fixed effect for the lender.

The next step in analyzing the impact of different funding structures on credit supply involves integrating equations (2) and (3). This allows us to directly assess how variations in funding structures translate into changes in credit availability. Formally, we estimate:

$$(4)\ \log(consumer\ debt)_{i,t,l} = \alpha_{i,t} + \beta_1 monetary\_policy\_surprise_{t-m} + \beta_2 fund\_share_{t-m,l} + \beta_3 monetary\_policy\_surprise_{t-m} \times fund\_share_{t-m,l} + \beta_4 monetary\_policy\_surprise_{t-m} \times non\_bank_l + \beta_5 monetary\_policy\_surprise_{t-m} \times fund\_share_{t-m,l} \times non\_bank_l + \delta macro\_controls_t + \lambda_l + \varepsilon_{i,t,l}$$

[5] Since the risk indicators are at the borrower level, these indicators, without the interactions, are absorbed by the individual fixed effect.

In this specification we include the share of a funding component in lender's l total balance, and interact it with both monetary policy surprise and non_bank, the NBFI indicator. If $\beta_5 > 0$, we can conclude that monetary policy surprises affect credit from NBFIs with higher share of the examined funding component. While for this estimation we use bank and NBFI borrowers, as in equation (2), we also estimate an alternative version using only NBFI borrowers:

$$(4') \quad \log(consumer\ debt)_{i,t,l} = \alpha_i + \beta_1 monetary\_policy\_surprise_{t-m} + \beta_2 fund\_share_{t-m,l} + \beta_3 monetary\_policy\_surprise_{t-m} \times fund\_share_{t-m,l} + \delta macro\_controls_t + \varepsilon_{i,t,l}$$

In this specification we avoid the less interpretable triple interaction and our coefficient of interest is β_3. The cost in terms of identification is the use of only one observation per month for each borrower, thus giving up the inclusion of borrower-time fixed effect and using only borrower fixed effect.

3.3. The bank-NBFI nexus

In the last set of estimations, we aim to reveal the direct contribution of banks to the growth in NBFIs following monetary policy surprises. Using proprietary data on credit amount banks provide to NBFIs we establish the link between bank funding and NBFI consumer credit growth in two stages. First, we demonstrate how banks, in response to unexpected changes in monetary policy, increase their lending to NBFIs. We do this by estimating the following equation:

$$(5) \ \Delta funding_{l,t} = \alpha_l + \beta_1 monetary\_policy\_surprise_{t-m} \times \Delta bank\_credit_{t-m,l} + \delta macro\_controls_t + \lambda_l + \varepsilon_{l,t}$$

The dependent variable is one of four funding components as explained above. The new independent variable is $\Delta bank\_credit_{t-m}$ which measures the log-difference in credit from the banking system at time *t-m* to NBFI l. We combine this variable with the monetary policy surprise variable to measure the extent to which an increase in credit flows from banks to nonbank financial institutions (NBFIs), following an unexpected change in monetary policy, impacts a specific funding component of NBFIs.

Last, we connect bank credit to NBFIs and consumer credit directly by estimating the following equation:

$$(6) \ log(consumer\ debt)_{i,t,l} = \alpha_i + \beta_1 monetary\_policy\_surprise_{t-m} + \beta_2 \Delta credit\_from\_banks_{l,t-m+n} + \beta_3 monetary\_policy\_surprise_{t-m} \times \Delta credit\_from\_banks_{l,t-m+n} + \delta macro\_controls_t + \lambda_l + \varepsilon_{i,t,l}$$

In this equation, the main variable of interest is the interaction between the monetary policy surprise and the change in the extent to which the banking system lends to NBFI

l. The subscript *n* addresses the relative timing of the surprise and banks' lending, and its specific value is determined by the estimation results of equation (5). Since the focus now is NBFI lending and not the shift of share in credit between banks and NBFIs, we use only the debt each individual has to NBFIs at time t, and replacing the borrower-time fixed effect with borrower fixed effect.

4. Descriptive Statistics

4.1. Main developments

Our sample period extends from the beginning of 2021 to September 2023. We select 2021 as the starting point because it is less affected by the distortions caused by economic policies implemented in response to the COVID-19 crisis. We choose September 2023 as the endpoint because in October of that year, the Swords of Iron War broke out, with its substantial implications for the economy. In the left panel of Figure 1, we present the balance of total consumer credit to households by source, alongside the Bank of Israel's declared interest rate during the sample period. As can be observed, from the beginning of 2021, with the recovery from the COVID-19 crisis, there was an increase in bank credit to households; however, this growth halted in mid-2022 with the commencement of interest rate hikes, and the trend subsequently reversed. Concurrently, from mid-2022, a sharp increase in nonbank credit to households was observed, continuing until the end of the sample period. This pattern persists even when excluding auto loans (Figure 1, right panel), which we do not include in our analysis.

Figure 2 illustrates the development of each of the three components constituting total consumer credit: loans, utilization of current account credit facilities (overdrafts), and utilization of revolving credit facilities. The figure reveals that the dynamics described above regarding bank credit are present especially in loans, which consists the majority of bank credit—almost 80 percent of bank credit, on average, throughout the sample period. In contrast, bank credit provided through revolving credit facilities or overdraft continued to increase, though their share is around 20 percent of overall bank credit. In NBFI credit, however, most of the credit is provided through revolving credit facilities, and this amount started to increase before the beginning of the interest rates hikes and accelerated after they started.

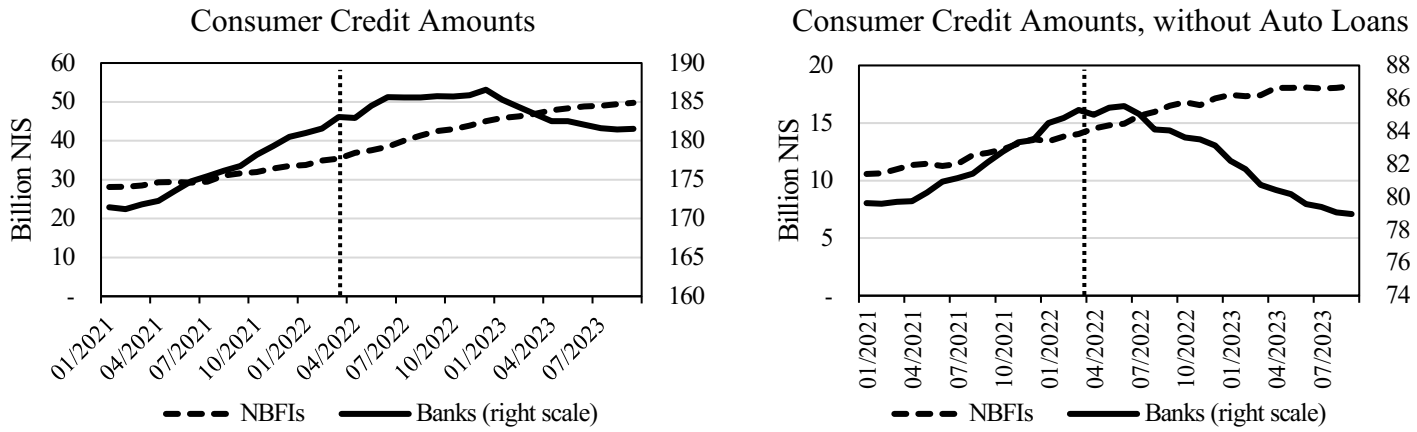

Figure 1. Aggregate credit amounts, in NIS billion, Jan. 2021–Sep. 2023. This figure presents the development of consumer credit, by its source—banks or NBFIs. The initiation of the cycle of monetary tightening is marked with a dotted line.

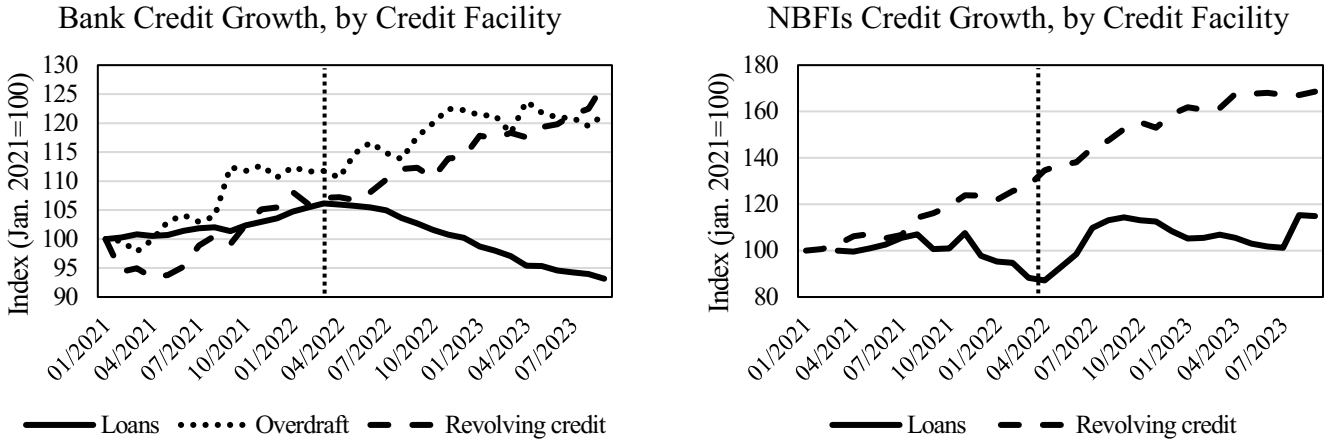

Figure 2. Credit growth, by facility, Jan. 2021–Sep. 2023. This figure presents the growth in each credit facility from each type of lender. The initiation of the cycle of monetary tightening is marked with a dotted line.

4.2. Sample Selection and Descriptive Statistics

From the full Register, we extract for each month of the sample period borrowers with a positive balance in any credit facility (excluding mortgages and auto loans) and in at least one bank and one NBFI. During most the sample period, the overall number of lenders in this sample is 24, of which 11 lenders are banks and 13 NBFIs.[6]

In Table 2, we reflect the proportion of this subpopulation within the entire Register population during the two central periods of our sample period: the period before interest rate increases began (from early 2021 to March 2022) and the period from the beginning of rate increases until the end of the sample period (April 2022 to September 2023). Panel A of the table presents the average number of borrowers in each period

[6] During the sample period, two NBFIs entered the Register. However, their size is relatively small and the analyses in the paper do not change if we exclude them and analyze only the set of stable lenders.

according to different compositions of lenders. The total number of borrowers in the Register, regardless of their lender composition, amounts to approximately 3 million individuals, with a growth of 7.9 percent between the two periods (column 1). The majority have at least one transaction with a bank (column 2), and 31 percent have at least one transaction with an NBFI (column 3). The population we will use for our estimations is presented in column 4. This population grew by 18.8 percent between the periods and constitutes 23.4 percent of the total population in the Register in the late period. The growth rate between periods significantly exceeds the growth in the total population.

Panel B describes the differences in average credit balance between the various populations and between the different periods. The population we are using has a slightly larger average credit balance, and this balance increased between periods, surpassing the growth in credit balance of the entire Register population. In Panel C and D we show the average number of credit facilities and lenders of each borrower, respectively. The overall Register population holds almost 2 credit facilities and 35 percent have more than one borrower. The population of our interest hold 2.6 credit facilities on average, and have 2.5 lenders.

In Table 3, we examine the degree of representativeness of our focus sub-population relative to the entire Register population. We characterize borrowers based on socio-demographic variables – age group and socioeconomic level of their residential locality – and variables from the database reflecting financial behavior and risk profile: proportion of mortgage holders, proportion of overdraft users, proportion with delinquency in one of their loans, and proportion of loans for micro-businesses. The table indicates that our sub-population has a higher representation of the 40-64 age group, middle socio-demographic deciles (4-7), mortgage holders, overdraft users, and loans for micro-businesses. The last two indicators suggest that, on average, borrowers who simultaneously borrow from both banks and NBFIs are slightly more risky.

Although interest rates are not the focus of this paper, we report the distribution of interest rate types and average rates for each sub-population. The differences between the two groups are more pronounced in the level of rates than in their composition – borrowers who simultaneously hold credit from both banks and NBFIs pay an average rate nearly two percentage points higher than the general Register population, consistent with their higher risk profile.

Table 2. Descriptive statistics of the population and sample

	All borrowers	Borrowers with at least one transaction with a bank	Borrowers with at least one transaction with a NBFI	Borrowers with at least one transaction with a bank and a NBFI
Panel A: Number of borrowers				
Jan. 2021 – Mar. 2022	2,994,154	2,757,590 (92.1%)	927,585 (31.0%)	637,423 (21.3%)
Apr. 2022 – Sep. 2023	3,230,559	2,968,024 (91.9%)	1,089,829 (33.7%)	757,499 (23.4%)
% growth between periods	7.9%	7.6%	17.5%	18.8%
Panel B: Average credit balance per borrower (NIS)				
Jan. 2021 – Mar. 2022	69,472	71,932	64,211	72,793
Apr. 2022 – Sep. 2023	69,725	72,183	68,012	76,984
% growth between periods	0.4%	0.3%	5.9%	5.8%
Panel C: Average number of credit facilities per borrower				
Jan. 2021 – Mar. 2022	1.94	1.98	2.40	2.61
Apr. 2022 – Sep. 2023	1.95	1.98	2.43	2.66
% growth between periods	0.2%	0.3%	1.4%	1.8%
Panel D: Average number of lenders per borrower				
Jan. 2021 – Mar. 2022	1.35	1.36	1.69	2.51
Apr. 2022 – Sep. 2023	1.37	1.38	1.75	2.52
% growth between periods	1.8%	1.9%	3.3%	0.2%

This table presents descriptive statistics of the population in the Register and in the sub-population consisting the sample.

Table 3. Distribution of the population and sample by demographic and risk characteristics

	All borrowers	Borrowers with at least one transaction with a bank and a NBFI
Panel A: Age groups		
18-39	33%	30%
40-64	47%	54%
65+	20%	16%
Panel B: Socioeconomic level (1=lowest)		
1-3	23%	21%
4-5	23%	25%
6-7	32%	34%
8-10	22%	21%
Panel C: Borrowers who…		
… have a mortgage	33%	39%
… have an overdraft	56%	74%
… have a delinquency	3%	4%
… borrow for their micro-business	9%	13%
Panel D: Interest rates[7]		
Floating interest rate		
Share	84.7%	83%
Interest rate	6.8%	8.6%
Fixed interest rate		
Share	8.4%	12.2%
Interest rate	7.8%	9.6%

This table presents the distribution of the population in the Register and in the sub-population consisting the sample by demographic and risk characteristics.

As a measure of monetary policy surprises, we utilize the interest rate surprise series calculated by Kutai (2023). This methodological approach decomposes each interest rate decision into anticipated and unanticipated components by using the one-month or three-month TELBOR (Tel Aviv Interbank Offered Rate) as a proxy for market expectations of the policy rate. In one version, the surprise is calculated only for the interest rate declared at the same month the surprise occurred; in a second version, surprise is calculated for the path of the interest rate in the three coming months. Between January 2021 and September 2023, the Bank of Israel made 22 interest rate decisions. For 2 of these decisions, data limitations prevented the determination of any surprise element. Among the remaining decisions, 11 contained a surprise component in either direction. Notably, the majority of these surprises (7 out of 11) were positive, indicating that the Bank of Israel implemented policy changes that were more hawkish than market expectations—either raising rates more than anticipated or cutting rates less than forecasted.

[7] We report only interest rates on payments that are not indexed to the CPI, floating and fixed. These consists the vast majority of interest rates types.

5. Results

5.1. Monetary Policy Effect on NBFI Credit

5.1.1. Main Results

We estimate the shift in the composition of consumer debt following monetary tightening by estimating equation (2) for each m=2,3,…,24 This framework and the use of current credit balance instead of credit growth gauges the dynamic effect of monetary policy on credit composition and utilizes the (relatively) high frequency of our data, while the inclusion of borrower-month fixed effect insures that the effect is attributed to changes in credit supply. We cluster the standard errors by lender. While Driscoll-Kraay standard errors address cross-sectional dependence and autocorrelation in panel data, we use clustered standard errors by lender for two main reasons. First, Driscoll-Kraay is designed for macro panels with long time series and few cross-sectional units, whereas our setting has millions of observations across 24 lenders over 33 months—a large-N, small-T structure. Second, our economic setting suggests observations are correlated within lenders due to common lending policies, but lenders operate with substantial independence, making within-cluster dependence the primary concern. Therefore, we cluster standard errors within lender. As a robustness check, we re-estimated our main specifications using Driscoll-Kraay standard errors and found qualitatively identical results (available upon request). The estimated coefficients for each lag and their 95% confidence intervals are presented in Figure 3. The full estimation results are in Table A.1 and A.2 in Appendix A.

The blue line reflects the estimated effect on NBFI credit from a surprise in the monthly interest rate while the red line is based on surprises to the 3-month interest rate path. In both versions, the immediate effect (that is, after 2 months) is positive and significant, indicating that an unexpected monetary tightening leads to a shift of credit balance towards NBFIs. The effect gets stronger with time, and reaches the maximum about 12 months after the surprise. Then, it gets weaker and disappears after about 18 months. Using the coefficient of the 12^{th} lag and multiplying it by the standard deviation of monetary surprises (0.05) leads to the conclusion that at the maximum, one standard deviation of a monetary policy surprise results 12 months later in a 2.8 percent increase in the share of NBFI credit in overall consumer credit.

To evaluate how much monetary policy shocks contributed to the increase in NBFIs' credit share over the entire period, we multiply the size of the surprise in each monetary policy decision by the relevant impulse response coefficient corresponding to the month of the decision relative to the end of our sample period (September 2023), and sum these products. We then compare the result to the overall growth in NBFIs' credit share in the consumer credit market. According to the data presented in the right panel of Figure 1, NBFIs' credit share increased from 15.7 percent in January 2021 to 21.5 percent in September 2023, a growth of 36 percent. The sum of the products of the surprises and the relevant impulse response coefficients amounts to 21.3 percentage points, which accounts for 58.1 percent of the overall growth in NBFIs' credit share in the consumer credit market.

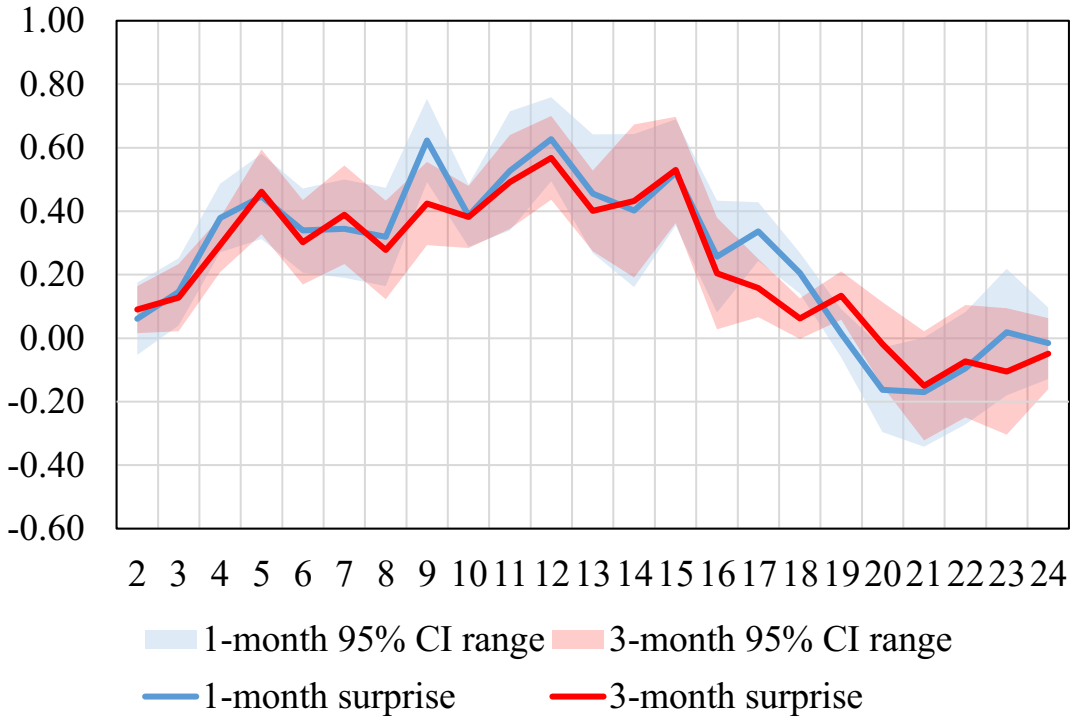

Figure 3. The estimated effect of monetary policy surprises on NBFIs' share in the consumer credit market. This figure presents the coefficients estimated by equation (2), for lags between 2 and 18 months. The blue line corresponds to estimations using the 1-month monetary policy surprise and the red line to the 3-month surprise. Shaded areas represent 95% confidence intervals.

One possible explanation for this result might be that following monetary tightening, banks become more risk averse and avoid lending to risky borrowers, while NBFIs increase credit to those riskier borrowers. If this risk taking channel is what drives our result, we would expect that risk indicators would explain, at least partly, the increase in the share of NBFIs' credit. We test this by estimating equation (2A), in which we include all available indicators for borrower's risk. These indicators include: 1) whether the borrower has any delinquency in one of his credit facilities; 2) whether the borrower has an overdraft; 3) whether the purpose of the credit is the micro-business the borrower owns. The indicators are calculated at the borrower level and for each month, and enter the regression as an interaction with monetary policy surprise, and as an interaction with both monetary policy surprise and the NBFI indicator.

Estimation results (provided in Appendix B) show that the interaction between monetary policy surprise and NBFI indicator remain positive and significant, and that all triple interactions between risk indicator, monetary policy surprises and NBFI are negative and significant. This implies that not only do monetary policy surprises lead to greater share of NBFI credit, this increase is not a result of risk-taking by NBFIs. In fact, the results show that monetary policy surprises lead NBFIs to decrease their exposure to risky borrowers. The results do not change for higher values of h or when we use the 3-month interest rate path surprise.

5.1.2. Robustness Tests

Two potential concerns regarding the robustness of the main results warrant consideration. First, by restricting the estimation sample to borrowers with outstanding credit from both types of lenders simultaneously, we exclude borrowers who added or dropped a credit source during the sample period. In particular, borrowers who fully repaid their NBFI debt following monetary tightening are absent from the sample, potentially introducing survival bias, as estimation is conditioned on borrowers maintaining active credit relationships with both banks and NBFIs throughout the period. Second, using log-levels of credit balances as the dependent variable may yield biased estimates if a time trend affects the composition of the credit market. While borrower-time fixed effects partially mitigate this concern, they do not fully resolve it.

We address both issues through the construction of a pairwise balanced panel. Specifically, for each horizon m, we construct a balanced panel of borrower-lender pairs and impute missing credit balances with zeros. To illustrate, consider a borrower who holds outstanding credit from both a bank and an NBFI at time t, but whose NBFI balance is fully repaid by time $t+m$, leaving only a bank relationship active. In the baseline specification, this borrower appears only at time t; in the balanced panel, the borrower is retained at both periods, with the NBFI credit balance set to zero at $t+m$. Beyond resolving survival bias, this construction enables the use of first-differenced log credit balances as the dependent variable, thereby eliminating any time trend that might otherwise affect the results.

While this specification is arguably more comprehensive, it entails an important identification trade-off that limits its use to a robustness check. In the baseline specification, borrower-time fixed effects absorb all time-varying borrower-level demand factors. In the balanced panel with a differenced dependent variable, however, borrower-time fixed effects cannot be included jointly with first-differencing, as doing so eliminates all within-borrower variation, leaving only time-series variation for identification. The two must therefore be used separately.

Taken together, we re-estimate an adjusted version of equation (2) on the pairwise balanced panel using first-differenced log credit balances as the dependent variable, within a local projection framework (Jordà, 2005). The resulting impulse response functions are presented in Figure 4, with full estimation results reported in Appendix C. The findings are consistent with the baseline: the effect of monetary policy surprises on NBFI credit growth is positive and statistically significant, peaking approximately twelve months after the surprise.

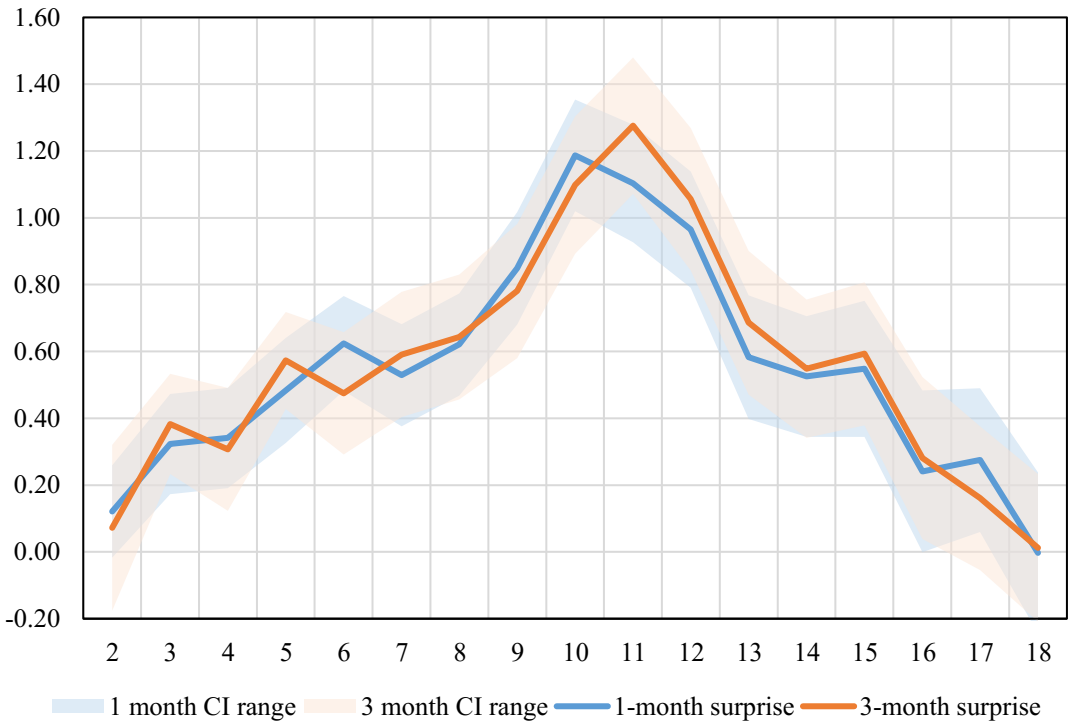

Figure 4. Local projection of the effect of monetary policy surprises on NBFIs' share in the consumer credit market. This figure presents the estimated effect of monetary policy surprise on NBFI credit, as estimated by the adjustment of equation (2). The coefficients presented are an estimation of the effect for lags between 2 and 18. The blue line presents the estimation when using the 1-month monetary policy surprise and the red line is obtained from using the 3-months surprise for estimation. Shaded areas present the 95% confidence intervals.

A second robustness concern relates to lending capacity constraints at banks. Some borrowers may have exhausted their borrowing capacity at a bank upon taking out a mortgage, subsequently turning to NBFIs for consumer credit. If this conduct is prevalent, the estimated compositional shift may reflect supply-side constraints at the individual borrower level rather than a differential institutional response to monetary tightening. To address this, we re-estimate equation (2) restricting the sample to borrowers who already held a mortgage at the start of the sample period, thereby holding constant any variation in bank lending capacity arising from new mortgage originations during the sample. The estimated coefficients and their 95% confidence intervals, presented in Figure 5 (and full results in Appendix D), confirm that the main results are robust to this restriction.

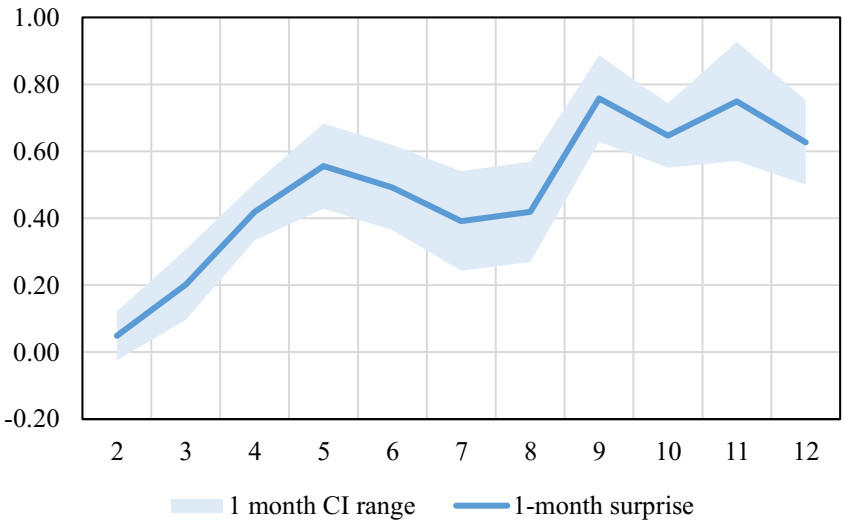

Figure 5. The estimated effect of monetary policy surprises on NBFIs' share in the consumer credit market among incumbent mortgage lenders. This figure presents the estimated effect of monetary policy surprise on NBFI credit, as estimated by equation (2), using the sub-sample of borrowers who had an existing mortgage prior to the sample period. The coefficients presented are an estimation of β_1 for lags between 2 and 12. The blue line presents the estimation when using the 1-month monetary policy surprise. Shaded areas present the 95% confidence intervals.

5.2. Lender's funding structure and the bank—NBFI nexus

We now turn to estimate the relation between the funding structure of banks and NBFIs and how it maps into consumer credit they provide. We begin by reporting the aggregate funding structure of these two groups of institutions before and after the interest rate hikes (Figure 6). At the end of 2021, NBFIs held twice as much equity than banks held. This result implies that NBFIs have lower leverage, a well-documented result that reflects banks' easier access to unsecured deposits as a main source of funding due to explicit or implies deposit insurance (e.g., Jiang, Matvos, Piskorski and Seru, 2023). The figure also shows that the share of long-term liabilities was similar for banks and NBFIs. However, after the cycle of interest rate hikes, NBFIs increased the share of long-term liabilities in their funding structure while this share in banks decreased. Concurrently, the share of short-term liabilities in banks (mostly deposits), also increased.

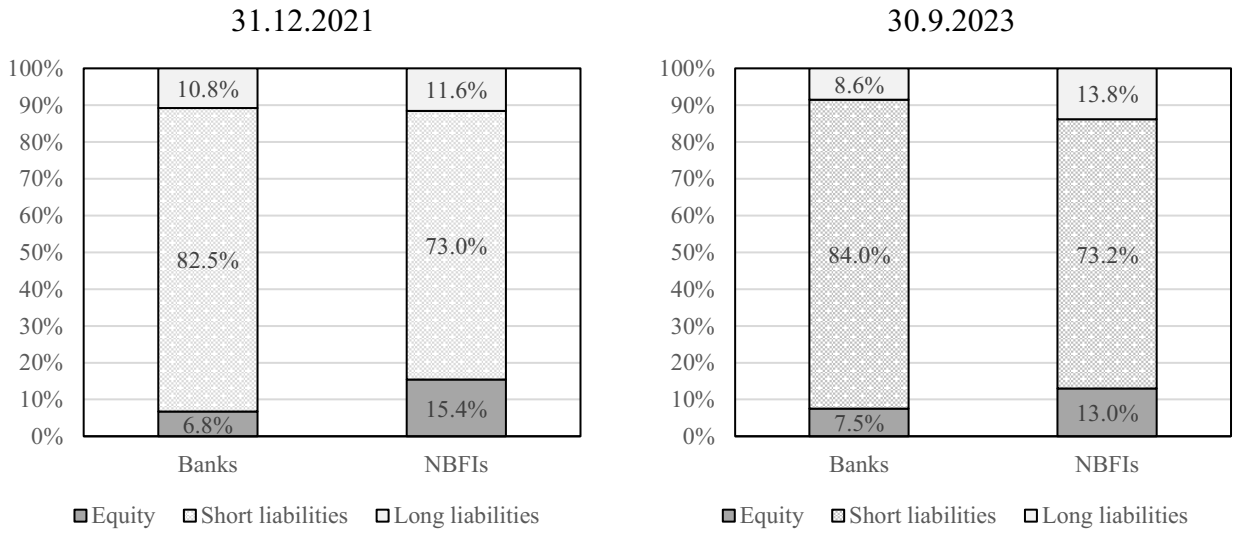

Figure 6. Funding structure of banks and NBFIs. This figure presents the funding structure of banks and NBFIs at the beginning of the sample period and at its end.

We formally support these developments by estimating equation (3), using data on amounts of equity, short- and long-term liabilities from banks' and NBFIs' quarterly financial reports for the period of 2008 to 2023. We convert monthly monetary surprises into quarterly terms by lagging the surprises by one month and then aggregating these lagged monthly surprises into by quarter (3 months). To simplify the interpretation, we run the model twice: first, using only data for banks, and then using only data for NBFIs.[8] As the dependent variable, we alternatively use the long-term liabilities, short-term liabilities, equity and non-short-term liabilities (equity plus long-term liabilities). The independent variable of interest is the monetary policy surprise, and its estimated coefficient is presented in Table 4. Results show that indeed NBFIs' long-term liabilities increase following a monetary policy surprise, while no similar effect is found for banks. As for other funding components, short-term liabilities decrease for NBFIs with no effect observed in banks, while equity shows a similar pattern, though less significant and only after 3 lags. Overall, non-short-term liabilities increase in NBFIs but do not change in banks. These results confirm that indeed long-term liabilities (or, generally, non-short-term liabilities) are flowing into NBFIs after monetary policy surprises.

In comparing our findings with those of Cucic and Gorea (2024), a notable observation emerges: monetary policy surprises have minimal impact on the funding structure of banks. We suggest that this is more consistent with the notion that overall, funds stay within banks, and with the fact that in Israel only banks take deposits. As for short-term liabilities deposits, when the interest rate increases, money market funds are becoming more attractive as they can offer higher yield for short-term funds. This is possible because these funds provide wholesale deposits to banks (either directly or through certificates of deposits), and in turn get better rates, which are passed on to their

[8] Results do not change if we pool banks and NBFIs together and include a dummy variable for NBFIs and their interactions with other independent variables.

investors.[9] Nevertheless, although the type of depositor has changed, the funds are still kept at the banking system. As for long-term liabilities, deposits are the main type of liability and they became more attractive after interest rate hikes, while other liabilities became more expensive, hence less attractive. These two effects may offset each other, which may explain why the effect of monetary surprises on long-term liabilities was found to be insignificant.

Table 4. The effect of monetary policy surprises on changes in the funding structure of banks and NBFIs.

Lag		Long-term liabilities	Short-term liabilities	Equity	Long-term funding
1	**Banks**	0.009	0.006	-0.009	0.005
		(0.009)	(0.006)	(0.005)	(0.006)
	Observations	593	593	0.04	593
	R-squared	0.38	0.63	0.51	0.5
	NBFIs	0.289***	-0.154***	-0.02	0.193***
		(0.021)	(0.042)	(0.012)	(0.026)
	Observations	365	383	383	383
	R-squared	0.07	0.01	0.06	0.03
2	**Banks**	0.015	0.016**	-0.007	0.009
		(0.009)	(0.006)	(0.005)	(0.006)
	Observations	593	593	593	593
	R-squared	0.38	0.63	0.51	0.49
	NBFIs	0.389***	-0.154***	-0.041*	0.203***
		(0.037)	(0.036)	(0.017)	(0.019)
	Observations	383	383	383	383
	R-squared	0.01	0.03	0.05	0.03
3	**Banks**	0.007	0.016	-0.008***	0.004
		(0.005)	(0.037)	(0.002)	(0.003)
	Observations	593	593	593	593
	R-squared	0.38	0.64	0.51	0.5
	NBFIs	0.179***	-0.143*	-0.066***	0.107***
		(0.045)	(0.062)	(0.015)	(0.026)
	Observations	365	383	383	383
	R-squared	0.07	0.02	0.05	0.02

This table presents estimation results of equation (3). The dependent variables is the change in the share of each one of the funding components, and the coefficient of interest is that of monetary policy surprises, which is presented for banks and NBFIs separately, and for different lags. Standard errors are in parentheses. *** indicates 1% significance, ** indicates 5% significance, and * indicates 10% significance.

While Cucic and Gorea (2024) propose that long-term liabilities exiting the banking system and subsequently flowing into nonbank financial institutions (NBFIs) serve as resources for NBFIs to expand their market share in credit markets, this raises a

[9] Money market funds also invest in commercial papers of financial institutions and Makam (central bank bills), but most of the trend in aggregate quantities comes from an increase in all type of bank deposits.

question: how can the increase in NBFIs' market share be explained when there is no substantial evidence of fund outflows from the banking system? We posit that the relationship between banks and NBFIs can elucidate these developments. To support this, we first examine the composition of NBFIs' debt by source—whether it originates from bank credit or corporate bonds (Figure 7). The figure clearly illustrates that bank credit experienced a significant increase towards the end of 2022, whereas the balance of debt raised through corporate bonds remained relatively stable. We support this claim by estimating equation (5), in which the dependent variable is one of the four funding components we defined above, and the independent variable of interest is the interaction between monetary policy and 1 plus the difference in the natural log of banks' credit to NBFI *l*.[10] Results in Table 5 confirm that following monetary policy surprises, banks lend more to NBFIs that use these funds to increase the share of long-term debt specifically.

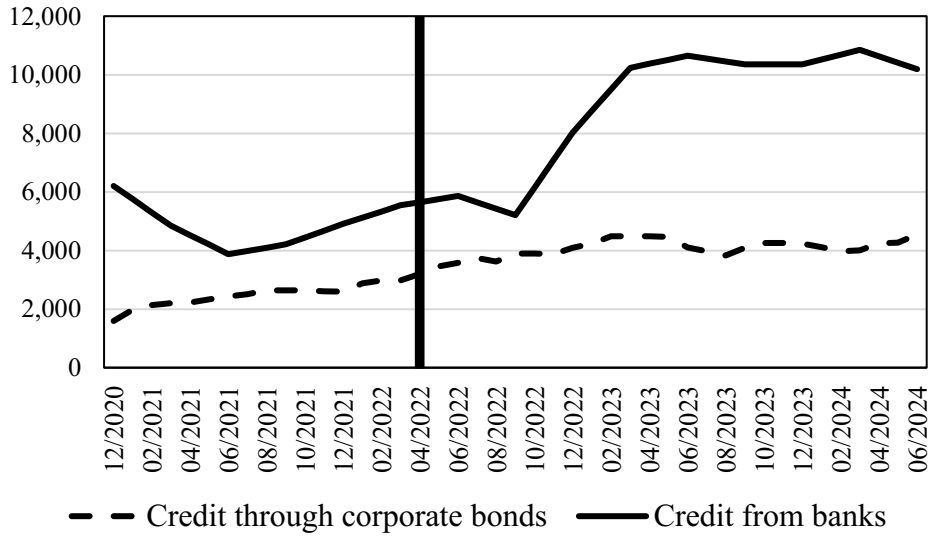

Figure 7. Credit sources of NBFIs, 2021–23. This figure presents the breakdown of NBFIs' overall credit into its two main sources – banks and corporate bonds (including commercial papers).

Table 5. NBFIs' bank credit and funding structure.

Lag	Long-term liabilities	Short-term liabilities	Equity	Long-term funding
1	0.065**	-0.068***	0.003*	0.068**
	(0.021)	(0.021)	(0.001)	(0.02)
Adj.R^2	0.508	0.515	0.719	0.516
2	0.047***	-0.05***	0.003**	0.05***
	(0.008)	(0.009)	(0.001)	(0.008)
Adj.R^2	0.495	0.503	0.718	0.503
3	0.11***	-0.11***	0.004*	0.11***

[10] We add 1 to the log-difference to prevent negative values, which could reduce the interpretability of the results.

	(0.026)	(0.024576	(0.002)	(0.024)
Adj.R^2	0.513	0.520	0.719	0.520
4	0.17*	-0.17***	0.002	0.18*
	(0.07)	(0.07)	(0.005)	(0.07)
Adj.R^2	0.533	0.538	0.716	0.537
5	0.06***	-0.06***	0.002	0.06***
	(0.005)	(0.005)	(0.002)	(0.005)
Adj.R^2	0.502	0.509	0.716	0.509

This table presents the estimated coefficient of the interaction between monetary policy surprises and banks' credit to NBFIs from estimating equation (5). The dependent variable in each column is the change in the share of each one of the funding components. Standard errors are in parentheses. *** indicates 1% significance, ** indicates 5% significance, and * indicates 10% significance.

We complete the estimation part by directly linking credit flows from banks to consumers through NBFIs following monetary tightening. We do this by estimating equation (6), which conceptually integrates equations (2) and (5). The population we use for estimation consists of most of the individuals we use for estimating equation (2),[11] however since we are interested only in their NBFI borrowing, we only use their debt balance in each NBFI from which they borrow. The variable of interest is again the interaction between monetary surprises and credit from banks to NBFI *l*, when the latter is defined as mentioned above. The lag structure of the variables reflect previous results: individual *i*'s debt balance at time *t* is explained by the interaction between a monetary policy surprise that occurred at time *t-m* and its interaction with the difference in bank credit that occurred 3 months later, i.e., at time *t-m+3*, where *t-m+3<t*.

In Table 6 we present estimation results of β_3, the coefficient of the interaction between surprises and credit from banks, for different values of *m*. Results show that indeed monetary policy surprises, and following an increase in bank credit to NBFIs, end in an increase of credit supply to consumers. The maximum effect is found to be 6 months after the shock, which leads to an increase in bank credit three months later, which in turn becomes credit to consumers three months later.

[11] The sample used here differs from that in equation (2), as it is restricted to borrowers whose nonbank lender's credit sources are identified. To verify that the baseline results carry over to this sub-sample, we re-estimate equation (2) accordingly and confirm that the positive relationship between monetary policy surprises and non-bank credit remains intact, as shown in Appendix E.

Table 6. The effect of bank credit to NBFIs on NBFIs' credit share

Lag:	4	5	6	7	8	9	10	11	12
β_3	0.042***	0.090***	0.246***	0.178***	0.111***	0.058***	-0.040***	-0.299***	-0.214***
	(0.008)	(0.007)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Macro controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,789,355	4,272,262	3,659,430	4,173,040	4,147,486	4,048,635	4,052,365	4,080,995	4,015,881
Adjusted R-square	0.708	0.713	0.729	0.715	0.714	0.721	0.719	0.72	0.718

This table presents the estimated coefficient of the interaction between monetary policy surprises and banks' credit to NBFIs. Standard errors are in parentheses. *** indicates 1% significance, ** indicates 5% significance, and * indicates 10% significance.

6. Conclusions

This paper provides novel microeconomic evidence on how monetary policy affects the composition of consumer credit markets between banks and NBFIs in Israel. Using borrower-month fixed effects and monetary policy surprises to address identification challenges, we demonstrate that monetary policy tightening leads to a significant shift in market share from banks to NBFIs. One standard deviation of a monetary policy surprise results in a 3.1 percent increase in NBFI credit share fourteen months later. Crucially, we identify the contribution of the funding structure for driving this effect: following monetary tightening, NBFIs increase their reliance on long-term financing while banks do not. Most importantly, we provide direct evidence that banks themselves facilitate this shift by increasing their lending to NBFIs following monetary tightening, which NBFIs then deploy to expand consumer credit. This bank-to-NBFI credit flow peaks six months after monetary surprises, and represents a previously underexplored transmission channel.

Our findings have important implications for monetary policy effectiveness and transmission mechanisms. The documented shift from banks to NBFIs following monetary tightening suggests that traditional models of monetary transmission, which focus primarily on bank credit channels, may underestimate the resilience of overall credit supply. When NBFIs expand their market share precisely when banks contract, the intended tightening effects of monetary policy on household credit are partially offset. This substitution effect implies that central banks may need to implement more aggressive policy adjustments to achieve desired macroeconomic outcomes, particularly in economies where NBFIs represent a substantial portion of the financial system. Furthermore, the fourteen-month lag between monetary surprises and peak NBFI market share expansion suggests that the full effects of monetary policy on credit composition take considerably longer to materialize than traditional bank-centric models would predict. Policymakers should therefore consider these extended dynamics when calibrating the timing and magnitude of interest rate adjustments, particularly during periods of financial stress when rapid policy transmission is crucial.

The discovery that banks actively finance NBFI expansion following monetary tightening reveals a complex web of financial interconnectedness, with significant implications for financial stability and regulatory oversight. Rather than representing independent alternatives to bank credit, our evidence suggests that NBFIs function as extensions of the banking system through funding relationships that intensify during monetary tightening. This interconnectedness means that risks ostensibly transferred from banks to NBFIs may not actually leave the banking system but rather be transformed and potentially amplified. The procyclical nature of bank lending to NBFIs – increasing precisely when interest rates rise to constrain credit – creates potential systemic risks that current regulatory frameworks may not adequately address. Banks may be using NBFIs as vehicles for regulatory arbitrage, effectively circumventing the intended effects of monetary tightening while maintaining exposure to consumer credit risk through their NBFI lending. This finding calls for enhanced regulatory coordination between banking supervisors and NBFI regulators, potentially including the development of consolidated supervision frameworks that account for these funding relationships. Policymakers should consider implementing measures to increase transparency in bank-NBFI funding relationships and may need to adjust regulatory capital requirements to reflect the true risk exposures that banks maintain through their NBFI lending activities.

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Appendix

Table A.1.

Variable \ Lag	2	3	4	5	6	7	8	9	10	11	12	13
NB x surprise	0.061	0.146	0.379***	0.446***	0.339**	0.345*	0.319*	0.623***	0.386***	0.527***	0.627***	0.455**
	[0.114]	[0.106]	[0.108]	[0.134]	[0.133]	[0.155]	[0.155]	[0.131]	[0.098]	[0.188]	[0.132]	[0.187]
NB x VIX	-0.021***	-0.017***	-0.004*	-0.022***	-0.019***	-0.007***	-0.002	-0.018***	-0.006**	-0.018***	-0.018***	-0.008***
	[0.004]	[0.004]	[0.002]	[0.004]	[0.004]	[0.002]	[0.003]	[0.004]	[0.002]	[0.004]	[0.003]	[0.003]
NB x Composite Index	-0.133***	-0.193***	-0.207***	-0.141***	-0.195***	-0.198***	-0.233***	-0.252***	-0.209***	-0.145***	-0.179***	-0.170***
	[0.015]	[0.025]	[0.022]	[0.016]	[0.028]	[0.024]	[0.027]	[0.029]	[0.022]	[0.016]	[0.026]	[0.022]
NB x Infl.-Expectations	0.022	0.015	0.069***	0.031	0.027	0.046	0.063	0.019	0.058**	0.012	0.015	0.042
	[0.015]	[0.023]	[0.025]	[0.020]	[0.025]	[0.030]	[0.023]	[0.019]	[0.028]	[0.020]	[0.024]	[0.028]
Nobs	18,993,383	18,896,198	18,988,382	18,922,986	18,874,080	18,971,174	18,047,264	19,050,350	19,160,346	19,069,465	19,010,029	19,093,742
Degree of freedom	11,439,580	11,379,821	11,435,598	11,397,530	11,367,400	11,425,450	10,869,763	11,472,692	11,539,222	11,484,803	11,448,593	11,499,495
R^2	0.515	0.516	0.515	0.515	0.516	0.515	0.515	0.516	0.515	0.516	0.516	0.515
R^2-*adj*	0.195	0.196	0.195	0.195	0.196	0.195	0.195	0.196	0.195	0.196	0.196	0.194

(continued)

Variable \ Lag	14	15	16	17	18	19	20	21	22	23	24
NB x surprise	0.402	0.522***	0.257	0.336***	0.205***	0.015	-0.163	-0.170	-0.095	0.019	-0.016
	[0.241]	[0.167]	[0.176]	[0.092]	[0.064]	[0.076]	[0.133]	[0.172]	[0.177]	[0.199]	[0.112]
NB x VIX	-0.021***	-0.018***	-0.004*	-0.022***	-0.020***	-0.006***	-0.019***	-0.022***	-0.014***	-0.020***	-0.016***
	[0.004]	[0.004]	[0.002]	[0.004]	[0.003]	[0.002]	[0.004]	[0.004]	[0.003]	[0.004]	[0.003]
NB x Composite Index	-0.140***	-0.197***	-0.206***	-0.144***	-0.202***	-0.204***	-0.160***	-0.179***	-0.162***	-0.154***	-0.222***
	[0.017]	[0.025]	[0.023]	[0.016]	[0.026]	[0.023]	[0.017]	[0.022]	[0.017]	[0.017]	[0.027]
NB x Infl.-Expectations	0.030	0.020	0.065*	0.037*	0.036	0.046	0.021	0.037*	0.010	0.024	0.009
	[0.022]	[0.015]	[0.033]	[0.021]	[0.026]	[0.030]	[0.020]	[0.022]	[0.022]	[0.020]	[0.025]
Nobs	19,020,844	18,950,733	19,026,498	18,964,117	18,891,437	18,975,469	18,901,353	18,875,158	18,986,816	18,876,987	18,829,979
Degree of freedom	11,456,383	11,413,875	11,459,571	11,423,551	11,378,601	11,428,051	11,384,573	11,367,520	11,434,081	11,367,963	11,339,215
R^2	0.515	0.516	0.515	0.515	0.516	0.515	0.515	0.516	0.516	0.515	0.516
R^2-*adj*	0.195	0.196	0.195	0.195	0.196	0.195	0.195	0.197	0.196	0.195	0.197

Table A.2.

Variable \ Lag	2	3	4	5	6	7	8	9	10	11	12	13
NB x surprise	0.090	0.128	0.294***	0.461***	0.302*	0.389*	0.278*	0.424***	0.382***	0.492***	0.568***	0.401***
	[0.074]	[0.106]	[0.086]	[0.134]	[0.133]	[0.155]	[0.155]	[0.131]	[0.098]	[0.148]	[0.132]	[0.127]
NB x VIX	-0.021***	-0.017***	-0.004	-0.022***	-0.019***	-0.007***	-0.002	-0.018***	-0.006*	-0.011***	-0.018***	-0.008***
	[0.004]	[0.004]	[0.002]	[0.004]	[0.004]	[0.002]	[0.003]	[0.004]	[0.002]	[0.000]	[0.003]	[0.003]
NB x Composite Index	-0.133***	-0.193***	-0.207***	-0.141***	-0.195***	-0.198***	-0.233***	-0.252***	-0.209***	-0.145***	-0.179***	-0.170***
	[0.002]	[0.025]	[0.022]	[0.016]	[0.028]	[0.024]	[0.027]	[0.029]	[0.022]	[0.016]	[0.026]	[0.022]
NB x Infl.-Expectations	0.022	0.015	0.069***	0.031	0.027	0.046	0.063	0.019	0.058**	0.012	0.078***	0.042
	[0.021]	[0.023]	[0.025]	[0.020]	[0.025]	[0.030]	[0.023]	[0.019]	[0.028]	[0.020]	[0.001]	[0.028]
Nobs	18,993,383	18,896,198	18,988,382	18,922,986	18,874,080	18,971,174	18,047,264	19,050,350	19,160,346	19,069,465	19,010,029	19,093,742
Degree of freedom	11,439,580	11,379,821	11,435,598	11,397,530	11,367,400	11,425,450	10,869,763	11,472,692	11,539,222	11,484,803	11,448,593	11,499,495
R^2	0.515	0.516	0.515	0.515	0.516	0.515	0.515	0.516	0.515	0.515	0.516	0.515
R^2-*adj*	0.195	0.196	0.195	0.195	0.196	0.195	0.195	0.196	0.195	0.194	0.196	0.194

(continued)

Variable \ Lag	14	15	16	17	18	19	20	21	22	23	24
NB x surprise	0.432*	0.530***	0.204	0.158*	0.062	0.134*	-0.019	-0.150	-0.095	-0.105	-0.049
	[0.241]	[0.167]	[0.176]	[0.092]	[0.064]	[0.076]	[0.133]	[0.172]	[0.177]	[0.199]	[0.112]
NB x VIX	-0.021***	-0.018***	-0.004*	-0.022***	-0.020***	-0.006***	-0.019***	-0.022***	-0.014***	-0.020***	-0.016***
	[0.004]	[0.004]	[0.002]	[0.004]	[0.003]	[0.002]	[0.004]	[0.004]	[0.003]	[0.004]	[0.003]
NB x Composite Index	-0.140***	-0.197***	-0.206***	-0.144***	-0.202***	-0.204***	-0.160***	-0.179***	-0.162***	-0.154***	-0.222***
	[0.017]	[0.025]	[0.023]	[0.016]	[0.026]	[0.023]	[0.017]	[0.022]	[0.017]	[0.017]	[0.027]
NB x Infl.-Expectations	0.030	0.020	0.065*	0.037***	0.036	0.046	0.021	0.037*	0.010	0.024	0.009
	[0.022]	[0.025]	[0.033]	[0.021]	[0.026]	[0.033]	[0.020]	[0.022]	[0.022]	[0.020]	[0.025]
Nobs	19,020,844	18,950,733	19,026,498	18,964,117	18,891,437	18,975,469	18,901,353	18,875,158	18,986,816	18,876,987	18,829,979
Degree of freedom	11,456,383	11,413,875	11,459,571	11,423,551	11,378,601	11,428,051	11,384,573	11,367,520	11,434,081	11,367,963	11,339,215
R^2	0.515	0.516	0.515	0.515	0.516	0.515	0.515	0.516	0.516	0.515	0.516
R^2-*adj*	0.195	0.196	0.195	0.195	0.196	0.195	0.195	0.197	0.196	0.195	0.197

Table B.1.

lag / Variable	2	3	4	5	6	7	8	9	10	11	12
NB x Surprise	1.134***	1.253***	1.433***	1.568***	1.503***	1.485***	1.319***	1.168***	1.025***	1.380***	1.088***
	[0.075]	[0.075]	[0.065]	[0.065]	[0.075]	[0.080]	[0.075]	[0.065]	[0.065]	[0.075]	[0.075]
NB x Surprise x Risk: overdraft	-0.015***	-0.016***	-0.014***	-0.017***	-0.018***	-0.016***	-0.011***	-0.008***	-0.008***	-0.013***	-0.010***
	[0.002]	[0.003]	[0.002]	[0.003]	[0.003]	[0.003]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
NB x Surprise x Risk: deliquency	-1.547***	-1.622***	-1.619***	-1.548***	-1.555***	-1.544***	-1.677***	-1.056***	-1.019***	-1.135***	-0.996***
	[0.291]	[0.295]	[0.295]	[0.291]	[0.291]	[0.291]	[0.291]	[0.280]	[0.285]	[0.291]	[0.291]
NB x Surprise x Risk: micro-business	-3.352***	-3.611***	-3.659***	-3.519***	-3.608***	-3.733***	-3.658***	-2.263***	-2.251***	-2.598***	-2.320***
	[0.155]	[0.155]	[0.155]	[0.155]	[0.155]	[0.155]	[0.155]	[0.155]	[0.155]	[0.155]	[0.155]
NB x VIX	-0.003***	0.002***	0.009***	0.002***	-0.001***	0.002***	0.009***	0.002***	0.003***	0.012***	0.002***
	[0.000]	[0.000]	[0.001]	[0.000]	[0.000]	[0.000]	[0.001]	[0.000]	[0.000]	[0.000]	[0.000]
NB x Comp-Index	-0.071***	-0.049***	-0.110***	-0.057***	-0.039***	-0.054***	-0.066***	-0.099***	-0.096***	-0.081***	-0.023***
	[0.010]	[0.011]	[0.012]	[0.009]	[0.005]	[0.006]	[0.007]	[0.007]	[0.007]	[0.008]	[0.005]
NB x Infl.-Expect	0.056***	0.077***	0.006**	0.056***	0.084***	0.064***	0.041***	0.062***	0.037***	0.017***	0.077***
	[0.010]	[0.008]	[0.008]	[0.011]	[0.011]	[0.009]	[0.007]	[0.008]	[0.006]	[0.004]	[0.008]
Nobs	18,095,583	17,992,195	18,085,530	18,020,752	17,953,781	18,039,549	17,109,081	18,101,846	18,205,102	17,256,349	17,205,437
Degree of freedom	10,900,188	10,836,769	10,893,099	10,855,181	10,813,541	10,865,104	10,305,681	10,901,973	10,965,097	10,393,775	10,362,495
R^2	0.528	0.529	0.528	0.528	0.529	0.529	0.528	0.528	0.528	0.527	0.528
R^2-*adj*	0.217	0.218	0.217	0.217	0.218	0.218	0.216	0.216	0.216	0.215	0.216

Table B.2.

lag / Variable	2	3	4	5	6	7	8	9	10	11	12
NB x Surprise	0.874***	0.953***	1.073***	1.237***	1.220***	1.219***	1.095***	1.080***	1.009***	1.295***	1.100***
	[0.075]	[0.075]	[0.065]	[0.065]	[0.075]	[0.080]	[0.075]	[0.065]	[0.065]	[0.075]	[0.075]
NB x Surprise x Risk: overdraft	-0.011***	-0.011***	-0.009***	-0.013***	-0.014***	-0.014***	-0.009***	-0.008***	-0.007***	-0.012***	-0.010***
	[0.002]	[0.003]	[0.002]	[0.003]	[0.003]	[0.003]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
NB x Surprise x Risk: deliquency	-1.212***	-1.240***	-1.245***	-1.182***	-1.185***	-1.154***	-1.378***	-1.034***	-1.009***	-1.064***	-0.997***
	[0.291]	[0.295]	[0.295]	[0.291]	[0.291]	[0.291]	[0.291]	[0.280]	[0.285]	[0.291]	[0.291]
NB x Surprise x Risk: micro-business	-2.597***	-2.754***	-2.795***	-2.713***	-2.780***	-2.846***	-2.986***	-2.261***	-2.278***	-2.493***	-2.428***
	[0.155]	[0.155]	[0.155]	[0.155]	[0.155]	[0.155]	[0.155]	[0.155]	[0.155]	[0.155]	[0.155]
NB x VIX	-0.003***	0.002***	0.008***	0.002***	0.000	0.002***	0.008***	0.002***	0.003***	0.011***	0.002***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
NB x Comp-Index	-0.071***	-0.049***	-0.111***	-0.056***	-0.032***	-0.045***	-0.063***	-0.092***	-0.097***	-0.081***	-0.018***
	[0.010]	[0.011]	[0.012]	[0.009]	[0.005]	[0.006]	[0.007]	[0.007]	[0.007]	[0.008]	[0.005]
NB x Infl.-Expect	0.056***	0.076***	0.005*	0.062***	0.085***	0.068***	0.043***	0.066***	0.036***	0.014***	0.081***
	[0.010]	[0.008]	[0.008]	[0.011]	[0.011]	[0.009]	[0.007]	[0.008]	[0.006]	[0.004]	[0.008]
Nobs	18,095,583	17,992,195	18,085,530	18,020,752	17,953,781	18,039,549	17,109,081	18,101,846	18,205,102	17,256,349	17,205,437
Degree of freedom	10,900,188	10,836,769	10,893,099	10,855,181	10,813,541	10,865,104	10,305,681	10,901,973	10,965,097	10,393,775	10,362,495
R^2	0.528	0.529	0.528	0.529	0.529	0.529	0.528	0.528	0.528	0.528	0.528
R^2 *-adj*	0.217	0.218	0.217	0.218	0.218	0.218	0.216	0.217	0.216	0.216	0.216

Table C.1.

Variable \ Lead	2	3	4	5	6	7	8	9	10
NB x surprise	0.121	0.323*	0.341*	0.483***	0.624**	0.529***	0.621***	0.849***	1.187***
	[0.117]	[0.127]	[0.127]	[0.128]	[0.137]	[0.137]	[0.127]	[0.147]	[0.147]
NB x VIX	-0.023***	-0.017***	-0.001	-0.018***	-0.016***	0.002	0.012***	-0.010***	0.004
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
NB x Composite Index	-0.103***	-0.220***	-0.260***	-0.210***	-0.277***	-0.300***	-0.343***	-0.400***	-0.209***
	[0.022]	[0.022]	[0.022]	[0.022]	[0.022]	[0.022]	[0.027]	[0.022]	[0.022]
NB x Infl.-Expectations	0.147***	0.137***	0.035	0.128***	0.132***	0.025	-0.014	0.102***	0.006
	[0.028]	[0.028]	[0.028]	[0.028]	[0.028]	[0.028]	[0.028]	[0.028]	[0.028]
Nobs	18,993,383	18,896,198	18,988,382	18,922,986	18,874,080	18,971,174	18,047,264	19,050,350	19,160,346
Degree of freedom	18,126,157	18,039,981	18,126,404	18,057,792	18,020,049	18,110,958	17,215,402	18,193,124	18,297,102
R^2	0.573	0.620	0.607	0.630	0.648	0.640	0.642	0.642	0.635
R^2-*adj*	0.553	0.602	0.588	0.613	0.631	0.623	0.625	0.625	0.618

(continue)

Variable \ Lead	11	12	13	14	15	16	17	18
NB x surprise	1.103***	0.965***	0.583**	0.525**	0.548**	0.241	0.275	-0.003
	[0.157]	[0.167]	[0.167]	[0.187]	[0.187]	[0.187]	[0.195]	[0.197]
NB x VIX	-0.011***	-0.014***	-0.005*	-0.019***	-0.017***	-0.003	-0.018***	-0.020***
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
NB x Composite Index	-0.229***	-0.253***	-0.230***	-0.218***	-0.278***	-0.260***	-0.222***	-0.258***
	[0.022]	[0.022]	[0.022]	[0.022]	[0.022]	[0.022]	[0.022]	[0.022]
NB x Infl.-Expectations	0.083***	0.105***	0.046	0.120***	0.113***	0.028	0.104***	0.120***
	[0.028]	[0.028]	[0.028]	[0.028]	[0.028]	[0.028]	[0.028]	[0.028]
Nobs	19,069,465	19,010,029	19,093,742	19,020,844	18,950,733	19,026,498	18,964,117	18,891,437
Degree of freedom	18,202,057	18,152,790	18,231,067	18,153,689	18,093,731	18,163,988	18,097,510	18,035,740
R^2	0.632	0.625	0.615	0.601	0.583	0.572	0.547	0.521
R^2-*adj*	0.614	0.607	0.597	0.582	0.564	0.552	0.526	0.498

Table C.2.

Variable \ Lead	2	3	4	5	6	7	8	9	10
NB x surprise	0.072	0.383**	0.307*	0.573***	0.475**	0.591***	0.643***	0.781***	1.098***
	[0.187]	[0.127]	[0.147]	[0.185]	[0.157]	[0.157]	[0.157]	[0.167]	[0.187]
NB x VIX	-0.023***	-0.017***	-0.001	-0.018***	-0.016***	0.002	0.012***	-0.010***	0.004
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
NB x Composite Index	-0.103***	-0.220***	-0.260***	-0.210***	-0.277***	-0.300***	-0.343***	-0.400***	-0.209***
	[0.022]	[0.022]	[0.022]	[0.022]	[0.022]	[0.022]	[0.027]	[0.022]	[0.022]
NB x Infl.-Expectations	0.147***	0.137***	0.035	0.128***	0.132***	0.025	-0.014	0.102***	0.006
	[0.028]	[0.028]	[0.028]	[0.028]	[0.028]	[0.028]	[0.028]	[0.028]	[0.028]
Nobs	18,993,383	18,896,198	18,988,382	18,922,986	18,874,080	18,971,174	18,047,264	19,050,350	19,160,346
Degree of freedom	18,126,157	18,039,981	18,126,404	18,057,792	18,020,049	18,110,958	17,215,402	18,193,124	18,297,102
R^2	0.573	0.620	0.607	0.630	0.648	0.640	0.642	0.642	0.635
R^2 *-adj*	0.553	0.602	0.588	0.613	0.631	0.623	0.625	0.625	0.618

(continue)

Variable \ Lead	11	12	13	14	15	16	17	18
NB x surprise	1.276***	1.056***	0.686***	0.548**	0.593**	0.281	0.161	0.012
	[0.187]	[0.195]	[0.197]	[0.197]	[0.187]	[0.187]	[0.197]	[0.197]
NB x VIX	-0.017***	-0.014***	-0.005*	-0.019***	-0.017***	-0.003	-0.018***	-0.020***
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
NB x Composite Index	-0.278***	-0.253***	-0.230***	-0.218***	-0.278***	-0.260***	-0.222***	-0.258***
	[0.022]	[0.022]	[0.022]	[0.022]	[0.022]	[0.022]	[0.022]	[0.022]
NB x Infl.-Expectations	0.113***	0.105***	0.046	0.120***	0.113***	0.028	0.104***	0.120***
	[0.028]	[0.028]	[0.028]	[0.028]	[0.028]	[0.028]	[0.028]	[0.028]
Nobs	19,069,465	19,010,029	19,093,742	19,020,844	18,950,733	19,026,498	18,964,117	18,891,437
Degree of freedom	18,202,057	18,152,790	18,231,067	18,153,689	18,093,731	18,163,988	18,097,510	18,035,740
R^2	0.613	0.625	0.615	0.601	0.583	0.572	0.547	0.521
R^2 *-adj*	0.594	0.607	0.597	0.582	0.564	0.552	0.526	0.498

Table D.1.

Variable \ Lag	2	3	4	5	6	7	8	9	10	11	12
NB x surprise	0.049	0.202	0.419***	0.556***	0.492***	0.392**	0.419**	0.758***	0.647***	0.749***	0.627***
	[0.073]	[0.105]	[0.085]	[0.127]	[0.127]	[0.149]	[0.150]	[0.129]	[0.096]	[0.178]	[0.126]
NB x VIX	-0.020***	-0.017***	-0.004	-0.021***	-0.019***	-0.007***	-0.002	-0.018***	-0.006**	-0.018***	-0.017***
	[0.004]	[0.004]	[0.002]	[0.004]	[0.004]	[0.002]	[0.002]	[0.004]	[0.002]	[0.004]	[0.003]
NB x Composite Index	-0.130***	-0.187***	-0.203***	-0.138***	-0.189***	-0.193***	-0.227***	-0.245***	-0.204***	-0.141***	-0.173***
	[0.016]	[0.025]	[0.023]	[0.016]	[0.028]	[0.025]	[0.028]	[0.030]	[0.023]	[0.016]	[0.026]
NB x Infl.-Expectations	0.023	0.017	0.067***	0.031	0.028	0.043	0.060***	0.02	0.055**	0.012	0.016
	[0.020]	[0.022]	[0.024]	[0.019]	[0.024]	[0.029]	[0.022]	[0.019]	[0.027]	[0.019]	[0.023]
Nobs	15,866,218	18,240,261	15,862,079	15,810,361	15,776,040	15,851,652	15,079,081	15,914,078	15,997,537	15,924,695	15,880,994
Degree of freedom	9,515,251	10,869,188	9,511,888	9,482,291	9,461,183	9,505,809	9,043,329	9,542,820	9,592,637	9,549,572	9,523,185
R^2	0.518	0.518	0.518	0.518	0.518	0.518	0.517	0.518	0.518	0.517	0.518
R^2 *-adj*	0.196	0.197	0.196	0.196	0.197	0.196	0.193	0.197	0.196	0.195	0.197

Table E.1.

Variable \ Lag	2	3	4	5	6	7	8	9	10	11	12
NB x surprise	0.055	0.179	0.419***	0.556***	0.492***	0.392**	0.419***	0.719***	0.659***	0.749***	0.627***
	[0.075]	[0.106]	[0.082]	[0.129]	[0.131]	[0.149]	[0.151]	[0.126]	[0.100]	[0.185]	[0.126]
NB x VIX	-0.020***	-0.017***	-0.021***	-0.022***	-0.019***	-0.006**	-0.001	-0.017***	-0.006**	-0.018***	-0.017***
	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	[0.003]	[0.003]	[0.004]	[0.003]	[0.004]	[0.004]
NB x Composite Index	-0.134***	-0.192***	-0.142***	-0.141***	-0.193***	-0.197***	-0.232***	-0.253***	-0.210***	-0.145***	-0.177***
	[0.015]	[0.025]	[0.016]	[0.016]	[0.029]	[0.025]	[0.028]	[0.029]	[0.023]	[0.016]	[0.026]
NB x Infl.-Expectations	0.026	0.020	0.035*	0.031	0.032	0.040	0.059***	0.022	0.052*	0.015	0.019
	[0.021]	[0.023]	[0.020]	[0.020]	[0.025]	[0.030]	[0.023]	[0.020]	[0.028]	[0.020]	[0.024]
Nobs	18,336,580	18,240,261	18,332,643	18,266,791	18,218,875	18,315,870	17,423,108	18,394,178	11,027,925	18,412,589	18,354,233
Degree of freedom	10,928,137	10,869,188	10,925,047	10,886,647	10,857,317	10,915,299	10,383,745	10,961,491	11,539,222	10,973,133	10,937,677
R^2	0.520	0.520	0.520	0.515	0.520	0.520	0.519	0.520	0.519	0.519	0.520
R^2 *-adj*	0.194	0.195	0.194	0.195	0.195	0.194	0.193	0.195	0.194	0.193	0.195