Currency Mismatch Exposures and Exchange Rate Shocks: Impact on the Bank lending channel*

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Abstract

Using Hungarian micro level data, we examine the role of currency mismatches on banks' balance sheets in the spillover of exchange rate shocks to local currency borrowers following the unexpected appreciation of the Swiss franc in January 2015. Direct currency mismatch on banks' balance sheets, measured by the net Swiss franc asset position, has a positive correlation with post-shock loan growth. Borrower currency mismatch on the bank balance sheet, measured by lending to unhedged borrowers, negatively affects loan growth. The response of individual banks to exchange rate shocks is heterogeneous and depends on the exposure structure of their balance sheets to two types of mismatches. Additionally, we provide evidence that variations in bank credit supply due to exchange rate shock have a significant impact on small firms' investment activity and their likelihood of default following the shock.

Keywords: bank lending channel, exchange rate, currency mismatch, credit registry

JEL Classification: F15, F21, F32, F36, G21.

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1 Introduction

Borrowing in foreign currency is widespread in emerging markets, and exchange rate fluctuations often lead to financial distress for unhedged borrowers. Open economy macroeconomics models indicate that currency mismatches - specifically, mismatches between local currency assets and unhedged foreign currency liabilities on borrowers' balance sheets - can connect exchange rate shocks to borrowers. This connection is called the "balance sheet effect". It emerges when the domestic currency depreciates, increasing the domestic currency value of foreign liabilities, subsequently weakens net worth and constrains firms' capacity to invest and expand (Krugman [1999], Céspedes et al. [2004]).

Existing empirical studies have mainly been concerned with the financial distress of foreign currency borrowers. However, it's also often been observed that local currency borrowers, who are not directly exposed to exchange rate risks, might also be affected after exchange rate shocks (Verner and Gyöngyösi [2020]). The role of financial intermediaries is crucial here, as they potentially spillover these shocks to local currency borrowers, and the broader real economy. Given mismatches on the bank balance sheets, these shocks can trigger changes in the capital and liquidity positions on banks' balance sheets, indirectly influencing firms via what is often referred to in literature as the "bank lending channel."

This paper investigates how the bank lending channel transmits exchange rate shocks to local currency borrowers and the broader economy, using micro-level data on banks and firs in Hungary. In emerging economies, the effects of an exchange rate shock on a bank mainly stem from two kinds of currency mismatches on their balance sheets. The first type, known as direct mismatch, is measured as the bank's net foreign currency asset position—the difference between foreign currency assets and liabilities. An exchange rate shock revalues this position, affecting the bank's net worth and liquidity[1]. The second type, the indirect currency mismatch, which involves loans in foreign currency to unhedged borrowers. Although these loans are recorded as foreign currency assets on the bank's balance sheet, they introduce significant mismatch risk for borrowers without stable income in foreign currency, and, thus increase the bank's credit risk. A sharp depreciation in the exchange rate can elevate the default likelihood of these loans due to "balance sheet effect", and consequently impacting the bank's asset returns (Ranciere

[1]This is similar to the previously mentioned "balance sheet effect," but at the bank level.

et al. [2010]).

Several recent studies have examined the effects of foreign currency risk on firms' (Kim et al. [2015], Kalemli-Ozcan et al. [2016]) and banks' balance sheets (Agarwal [2018], Abbassi and Bräuning [2021]). However, there's limited micro-level evidence on how currency mismatch exposure influences bank credit supply in emerging economies. Our study addresses this gap by investigating the bank lending channel of exchange rate shocks in Hungary, based on the Swiss franc appreciation in January 2015. This event is a suitable case study for two main reasons. First, the appreciation of Swiss franc was an unexpected external shock to Hungary. Secondly, Hungary, joint with other Central and Eastern European (CEE) countries, had significant "Swiss francization" before 2015. Hence, Swiss franc loans were prominent on banks' balance sheets and rely on wholesale funding to finance these loans. As a result, the Swiss franc appreciation likely had a substantial impact on Hungarian banks' balance sheets. We assess banks' exposure to direct mismatch by measuring their net Swiss franc asset position [2]. We measure the indirect mismatch by examining Swiss franc loans to unhedged borrowers. Both measurements were captured before the Swiss franc shock. It is crucial to clarify that our primary objective is to examine the effects of the two types of mismatch exposure, as derived from the literature, on credit supply following an exchange rate shock. Our intention is not to quantify the complete actual currency mismatch exposure for individual banks[3].

To study the bank lending channel of the exchange rate shock, we use within-firm difference-in-difference regressions, drawing on loan-level data from the Hungarian credit registry. This method helps us distinguish the effects of changes in credit supply from concurrent shifts in firms' credit demand and creditworthiness (Khwaja and Mian [2008]). From our loan-level analysis, several key findings emerge. By comparing lending to the same lo-

[2]In November 2014, the Hungarian Government introduced a conversion program to transit foreign currency household loans into Hungarian forint loans. This program has two relevant implications for our study: (1) The conversion program successfully protect households from exchange rate shocks. This help our identification strategy by allowing us to dismiss potential effects arising from household credit risk that might influence bank credit supply. (2) Although the program was implemented in February, the conversion rate was pegged to the market exchange rate at the time of the announcement. Consequently, when exchange rate shocks occur, household Swiss franc loans do not revalue in the same manner as other Swiss franc assets. To account for this discrepancy, we adjust the net Swiss franc asset position by excluding the total household Swiss franc loan amount.

[3]The full extent of a bank's actual currency mismatch depends on its balance sheet and off-balance sheet hedging.

cal currency borrowing firm from two banks—a difference of one standard deviation in their net Swiss franc asset positions—we find that the bank with a larger asset position increased its credit supply by 19% more than its counterpart. This indicates that a bank's net Swiss franc asset position directly affects its lending capacity post-shock. Banks with a higher asset position are better off after such shocks that raises the domestic currency value of foreign assets.

Whereas, our investigation based on the indirect mismatch measure found banks that extended more Swiss franc loans to unhedged firms saw a lower growth in local currency loans to the same firms than banks with fewer of these loans. Specifically, a one standard deviation rise in loans to unhedged firms correlated with a ten percentage point drop in loan growth post-shock. This reinforces the notion that banks with greater exposure to unhedged firms feel the adverse effects of exchange rate shocks more acutely. Considering the variations in net Swiss franc asset positions and lending volumes to unhedged firms among Hungarian banks, our findings highlight heterogeneous bank credit supply reactions to exchange rate shocks. Specifically, banks with notably positive net Swiss franc assets and fewer loans to unhedged firms tend to expand their credit. On the other hand, banks with negative net Swiss franc assets or more loans to unhedged firms typically contract their lending.

In our robustness tests, we account for potential influences from simultaneous other policy effects and external market funding conditions to validate our results. Specifically, we find that contemporaneous policy events such as compensation of household borrowers for excess interest rate charges from banks has no effect on our main results[4]. Our results are also not driven by the top ten percent larger size firms which can access to other external market funding. We also find that the two types of Swiss franc mismatches impact both the extensive margin and intensive margin of credit supply.

We further investigate the channels through which exchange rate shocks influence bank lending activities. Our analysis indicates that both types of mismatches are correlated with shifts in banks' net worth after the exchange rate shock. This suggests that the shock

[4]for the rest of the paper we refer to this policy event as 'interest rate compensation'

affected lending due to unexpected variations in capital adequacy, leading financial intermediaries to adjust their behaviour. By utilizing regression with interaction terms, we further highlight that the effects of both mismatches are more pronounced for firms that borrow from less liquid banks. This observation implies that the revaluation of net asset positions and excess credit losses from Swiss franc firm borrowers influence the bank's cash flow. This, in turn, affects liquidity conditions and credit supply. Conversely, banks with high liquidity seem to better manage the credit supply fluctuations driven by both mismatches.

Expanding on our loan-level analysis, we next examine how firm operations respond to exchange rate shocks via the bank lending channel. First, we determine the credit supply changes for each bank, induced by direct and indirect mismatches, using our loan-level results. We then compute the loan volume-weighted average to determine the change in credit supply at the firm level. This step allows us to measure the magnitude of credit supply change due to the exchange rate shock for individual firms. To counteract potential bias in the standard error of our firm-level regression, arising from the generated regressor problem, we employ a bootstrapping method. Our firm-level regression reveals that a one-standard-deviation drop in credit supply as a consequence of the the Swiss franc shock corresponds to an 18% reduction in overall bank borrowing growth for firms that borrow from multiple banks. This suggests that these firms cannot fully offset variations in credit supply simply by setting up new borrowing from other banks. Notably, this effect is significant only for smaller firms, suggesting that larger firms are more capable of managing fluctuations in credit supply. Next, we look at how variations in bank lending impact the real activities of firms. For firms that have loans from multiple banks, we find that changes in bank lending don't significantly affect their operational activities, even though these changes do impact their overall credit. This could be because these firms are generally larger and more profitable, allowing them to sustain their operations through internal funding. However, in the full sample which includes firms with multiple borrowing but is primarily made up of those with single borrowing, smaller firms display a positive correlation between credit supply and significantly reduce their possibilities of remaining solvent. For larger firms, changes in credit supply don't have a meaningful impact on their operations.

Related literature This paper contributes to the growing literature on the transmission mechanisms of exchange rate shocks through the bank lending channel. Closely related papers such as Agarwal [2018] and Abbassi and Bräuning [2021][5] explore the impact of exchange rate shocks on bank lending behavior due to currency mismatch in advanced economies. In contrast, our study has a specific focus on emerging markets[6]. We identify two types of mismatch exposures on bank balance sheets that are particularly relevant to emerging markets. The direct mismatch echoes findings from previous studies in this field. The indirect mismatch, however, has not been explored in the literature but holds significance in emerging economies due to the prevalence of foreign currency loans to unhedged borrowers, which poses systemic risk exposure for banks (Ranciere et al. [2010],Fischer and Yeşin [2022]). Our study also contributes to the literature on the spillover effects of macro shocks on unexposed lenders. For example, Huber [2018] show that bank lending contractions can negatively affect other local firms through demand spillovers. In contrast, we identify a reverse spillover channel. Specifically, we find that lending to unhedged foreign borrowers is associated with a post-exchange rate shock decline in credit supply. This suggests that the credit risk associated with foreign currency-exposed borrowers can impact a bank's balance sheet and, in turn, reduce the credit supply to other local currency borrowers.

Our analysis also connects with two main strands of literature: the first is the transmission of banking activities to the real economy. This literature includes many empirical studies showing that shocks to banks can lead to lending contractions that impact the real economy. For instance, studies like Khwaja and Mian [2008], Schnabl [2012], Cingano et al. [2016] have shown that firms borrowing from banks that experience declines in liquidity witness lower loan growth and investment. Similarly, research exploiting the European sovereign debt crisis (Popov and Van Horen [2015], De Marco [2019], Bottero et al. [2020]) illustrate the transmission of shocks through a contraction in credit. Conversely, some papers focus on positive shocks to banks (Jiménez et al. [2020]). Our study contributes to this strand of literature by demonstrating the crucial role of the bank lending channel in transmitting exchange rate shocks and establishing that the bank lending response can be contractionary or expansionary.

[5] Agarwal [2018] aligns with our concept of the direct mismatch, mainly explore the effect of the net foreign currency asset position on balance sheet. Abbassi and Bräuning [2021] consider the mismatch as both banks' on- and off-balance sheet net foreign currency positions.

[6] To our knowledge, this paper presents the first exploration of the role the bank lending channel plays in transmitting exchange rate shocks in emerging markets.

The second strand relates to foreign currency debt in international finance. The primary focus in this area has been on the implications of foreign currency indebtedness in the private or public sector (Krugman [1999], Chang and Velasco [2001], Schneider and Tornell [2004], Eichengreen et al. [2005], De Ferra et al. [2020]). Notably, Verner and Gyöngyösi [2020] explored the variation in exposure to household foreign currency debt during Hungary's late-2008 currency crisis. We extend the literature by demonstrating how local currency borrowers can also be significantly impacted through the bank lending channel following an exchange rate shock.

The paper is organized as follows. Section 2 offers institutional background and details the measurement of currency mismatch exposures. Section 3 discusses the empirical framework and presents summary statistics of the data. Sections 4 and 5 report the results of the bank lending channel analysis at the loan and firm levels, respectively. Finally, Section 6 concludes.

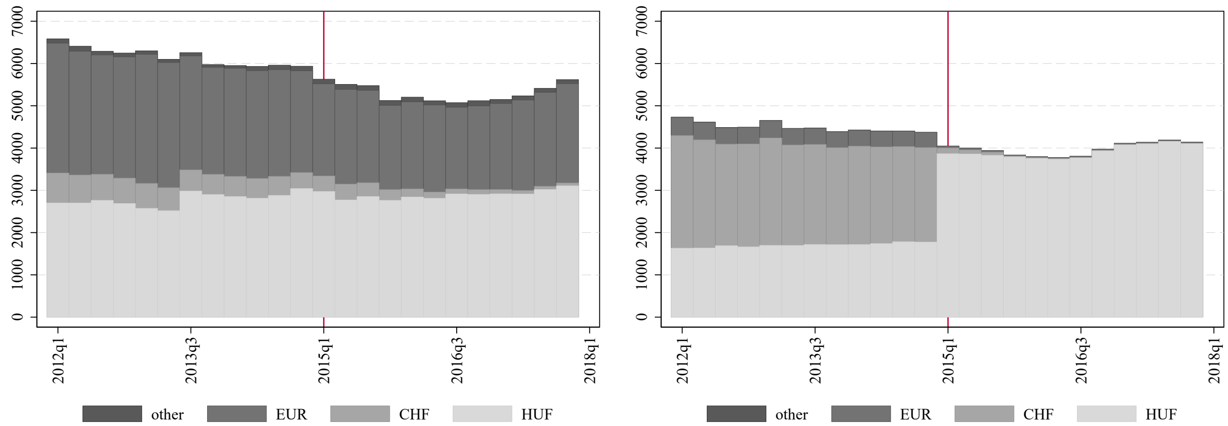
2 Institutional background and Currency mismatch exposures measurements

2.1 Institutional background

Before 2015, Central and Eastern European (CEE) countries, including Hungary, had significant exposure to Swiss franc currency risk. This exposure was a result of a high level of "Swiss francization" in both the asset and liability sides of the banks' balance sheets, meaning a large proportion of their financial obligations and assets were denominated in Swiss francs.[7] Particularly in Hungary, the foreign currency debt held by households and non-financial corporations accounted for about 50% of the total outstanding debt in 2014. (see Figure 1).

The stability of the Swiss franc-Hungarian forint exchange rate and lower interest rates

[7] Based on bank balance sheets in 2014Q4 the aggregated total Swiss franc assets to total assets is about 13%, the share of Swiss franc loans to total asset is 10.7%, and the share of Swiss franc liabilities to total assets is 3.4% for the 44 financial intermediaries in our sample.



(a) Corporate loan

(b) Household loan

Figure 1: The dynamic of private loans in Hungary

The figures show the evolution of private loans in Hungary. The figures contain 44 Hungarian banks in our sample and show the actual outstanding capital value of loans calculated with the end-of-quarter exchange rate. The quantities in X-axis are in Billion forints. Data source: MNB.

compared to local currencies in the pre-shock period were the factors which made Swiss franc-denominated loans an attractive option for borrowers in the CEE region. However, this created a significant currency mismatch, which became evident when the Swiss National Bank unexpectedly ended its policy of maintaining a minimum exchange rate of 1.2 Swiss francs per euro on January 15, 2015. This policy shift led to a rapid appreciation of the Swiss franc by almost 20% (as depicted in Figure 2), causing financial distress in economies with many unhedged borrowers in foreign currency.

The sudden and unanticipated exchange rate shock had a pronounced impact on the valuation of debt held by households and firms in the CEE countries, leading to an increase in non-performing loans on bank balance sheets (see also Fischer and Yeşin [2022]). The exposure to Swiss franc risk manifested in two specific mismatches in bank balance sheets: a direct mismatch, given by the net foreign asset position, and an indirect mismatch due to lending to unhedged borrowers.

Contrary to other CEE countries, Hungary introduced a timely and effective policy that helped policymakers to diminish the negative impacts of the Swiss franc shock on the Hungarian economy, especially within the household sector. On November 7, 2014, the

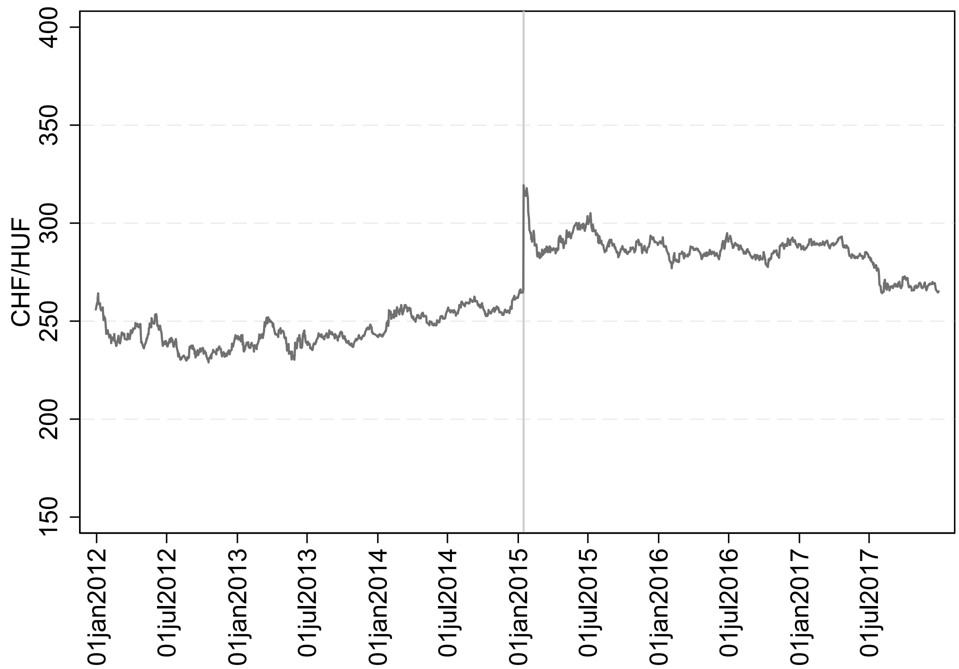


Figure 2: Exchange rate around the shock

This figure shows the daily nominal CHF/HUF exchange rates from 2012 to 2017.

Hungarian Parliament approved a bill allowing the Central Bank of Hungary to convert foreign currency household mortgage loans to Forint loans using foreign reserves. This policy, announced shortly before the Swiss franc exchange rate shock, effectively shielded the household sector from the subsequent currency shock. As a result, there were no household defaults on Swiss franc loans as seen in other CEE countries, thereby managing the risk of household demand distress.

This successful policy significantly curtailed the systemic exposure of the Hungarian banking system to Swiss franc fluctuations. Consequently, when the shock occurred, only two primary forms of exposure to the Swiss franc exchange rate shock left on Hungarian bank balance sheets. Firstly, loans to unhedged firms remained, which were still vulnerable to the Swiss franc variation. Secondly, despite the conversion program's announcement on November 7 and its predetermination to use the market rate from that day, the actual implementation of the program was only in February 2015. Thus, between these dates, Swiss franc household loans, while considered local currency assets economically, were still recorded as foreign currency assets in accounting terms. This discrepancy resulted in a mismatch between Swiss franc assets and liabilities in economic terms. The Central Bank of Hungary made considerable efforts to mitigate this mismatch risk, such as offering low-cost Euro swaps to banks and guiding them to manage the risk between the Euro and other currencies, including the Swiss franc. However, despite these measures, commercial banks couldn't perfectly hedge against the Swiss franc risk due to inaccurate predictions of the sudden depeg with Euro and their 'Regulatory Arbitrage' inclination[8]. Thus, even though the household sector was protected, banks and unhedged corporate borrowers remained at risk, spreading the effects of the Swiss franc shock throughout the Hungarian economy.

2.2 Hypotheses Development and Measurement of Currency Mismatch Exposure

In this section, we describe two channels through which exchange rate shock influence bank lending channel. Our study specifically focus the two channels relate to currency mismatch exposures found on banks' balance sheets and examines their impact on the lending channel.

The first channel is through a direct mismatch in Swiss francs on bank balance sheets, commonly known as the net Swiss franc asset position. When a bank possesses more assets in Swiss francs than liabilities, it maintains a positive net Swiss franc asset position. If this position is not perfectly hedged through off-balance sheet derivative contracts[9], a sudden rise in the Swiss franc's value can increase the bank's net asset value, thereby boosting its net worth[10]. Conversely, if a bank's Swiss franc liabilities exceed its assets, the

[8]Banks incline to defer or reduce the purchase of Swiss franc derivatives or only do so at the end of a quarter around regulatory fillings (Puriya and Bräuning [2021]), as a cost-saving measure, especially if they anticipated the Swiss franc would maintain peg with the Euro

[9]Banks can fix the exchange rate of these open positions using derivative contracts like forwards. However, these contracts can be costly. Two key factors can cause banks to hedge their net foreign asset positions imperfectly: first, as highlighted by Agarwal [2018], banks often estimate their risk based on historical data, which may not accurately predict future risks. In our context, banks might assume the Swiss franc and Euro will continue their peg from 2011, leading them to perceive the exchange risk is very low, particularly given the Central Bank of Hungary's provision of low-cost Euro/Forint swaps, which already addressed the risk between the Euro and Forint. Second, hedging necessitates collateral, which can be costly for banks. To save on costs, banks might either decrease the hedging amount or delay it until regulatory filings Puriya and Bräuning [2021].

[10]In empirical terms, a bank's net worth is typically quantified using metrics like the Tier 1 capital ratio or the capital adequacy ratio.

bank has a negative Swiss franc asset position. A similar appreciation of the Swiss franc can amplify the negative value of the imperfectly hedged net asset position, thus reducing the bank's net worth. This change has important implications for a bank's lending capacity. First, the revaluation can directly change the liquidity condition for banks, especially if their Swiss franc asset and liability are in short maturity or they have frequent Swiss franc interest gains and debt servicing, net value revaluation act like extra cash gain or payment for banks. Second, studies such as Bernanke and Gertler [1995] and Gertler and Kiyotaki [2010] highlight that the size of the external finance premium—a cost faced by borrowers in obtaining funds—limits the amount of credit that banks can supply, and it is inversely related to the net worth of banks. So, as the net worth of banks increases due to the exchange rate shock and a positive net Swiss franc position, it can secure outside funding at a lower cost and is less likely to face liquidity issues. This allows them to extend more credit. Moreover, this increased net worth provides a larger safety cushion or capital buffer for banks to absorb potential losses. Regulators or banks' own risk management policies often require this capital buffer to be at a certain level relative to the credit supply, a rule known as the capital constraint in banking literature. If a bank was already close to this limit before the exchange rate shock, an increase in net worth could ease this constraint, enabling the bank to increase its credit supply in the post-shock period.

The second channel is through borrower currency mismatches associated with Swiss franc-denominated corporate loans. These loans remain on bank balance sheets following the phase-out of households' foreign currency debt[11]. Of note, Switzerland was not among Hungary's top 20 export partners, accounting for a mere 0.95% of total Hungarian exports in 2014 according to the World Integrated Trade Solution (WITS). Consequently, it's likely that only a few firms held Swiss franc liabilities and simultaneously earned revenues in Swiss francs, leading to currency mismatches between income and liabilities on their balance sheets. When the domestic currency depreciates, these mismatches amplify the debt burden and create a contractionary impact on non-financial firms - a scenario commonly described as the "balance-sheet effect" in relevant literature. This balance-sheet effect can feedback onto banks through elevated credit loss provisions, potentially decreasing profitability (Bruno and Shin [2019], Niepmann and

[11] Sample data indicates that 95% of Swiss franc corporate loans present on bank balance sheets in 2014 originated before 2009. Appendix A.1 provides a breakdown by issuing year of Swiss franc corporate loans in 2014 from our 44 sample banks.

Schmidt-Eisenlohr [2022]). A drop in profits can lower the available cash and increase agency problems between banks and funding provider, making it even harder for banks to get funding.(Bolton and Freixas [2006], Van den Heuvel et al. [2002]). Moreover, banks often allocate their profits to establish "free" bank capital - capital that surpasses the minimum capital requirements - enabling them to finance profitable investments (Gambacorta and Shin [2018]). A hit to profitability can reduce this "free bank capital", leading to tighter minimum capital requirements and slower growth of credit supply in the post-shock period. Therefore, banks maintaining a higher share of Swiss franc-denominated corporate loans on their balance sheets are expected to decrease lending following the Swiss franc shock.

As we outlined above, in this paper, we focus on two types of Swiss franc mismatches which contribute to propagate exchange rate shocks to bank credit supply. The first type, which we refer to as the "direct" mismatch exposure, relates to the net Swiss franc asset position on bank balance sheets. The second type, or the "indirect" mismatch exposure, concerns mismatches on firm balance sheets. These can indirectly affect bank profitability and liquidity due to an increase in loan defaults following an exchange rate shock. We use the terms "direct" and "indirect" to distinguish these two types of exposures from the bank's perspective. It's crucial to highlight that the timing of the impacts from these mismatches varies. The direct mismatch instantly affects the bank's net worth at the time of the exchange rate shock, which we describe as the "stock" aspect. On the other hand, the indirect mismatch affects a bank's profitability and liquidity through increased loan defaults that occur after the shock – this is what we term as the "flow" aspect. Building on the discussion above, we can present the following two hypotheses:

- **Hypothesis 1**: Banks that had a higher exposure to the direct Swiss franc mismatch, i.e., a larger net Swiss franc asset position before the appreciation shock, were more likely to increase their credit supply in the period following the shock[12].
- **Hypothesis 2**: Banks that had a higher exposure to the indirect Swiss franc mismatch, i.e., more lending to unhedged firms before the appreciation shock, were more likely to decrease their credit supply in the period following the shock.

To validate our hypothesis, an accurate measurement of the extent of bank exposure to

[12] Hypothesis one is based on the assumption that direct Swiss franc mismatch exposure is not fully hedged.

these two specific types of Swiss franc mismatches on balance sheets is vital. The measurement should capture the sensitivity of a bank's balance sheet or income flows, or both, to fluctuations in the exchange rate Chui et al. [2016]. The larger this sensitivity, the more significant the currency mismatch. Despite the array of currency mismatches discussed in the literature, our study narrows its focus to these two specific Swiss franc mismatches and employs several unique measurement methods to identify them:

de jure Direct Mismatch

To quantify the direct mismatch for each bank, we employ the net foreign currency asset position definition, known as the *de jure* direct mismatch. This is calculated as the difference between the foreign currency-denominated assets and liabilities of a bank. Specifically, we define the direct mismatch for bank i as:

$$\text{DMismatch}_i^j = \frac{\text{CHF assets}_i - \text{CHF liabilities}_i}{\text{Total bank assets}_i} \tag{2.1}$$

If the assets and liabilities of a bank denominated in Swiss francs are equal, the value of DMismatch_i will be zero. This indicates that the balance sheet of bank i is not directly exposed to shocks in the Swiss franc exchange rate. When bank i has a positive net asset position in Swiss francs, an appreciation of the Swiss franc would beneficially impact its balance sheet, leading to an increase in net worth. The more significant the positive net asset position relative to total assets, the stronger this balance sheet effect. In our sample, almost all banks had a positive *de jure* direct Swiss franc mismatch position in Q4 2014[13].

de facto Direct Mismatch

The calculation of the *de jure* direct mismatch may not reflect the actual net Swiss franc asset position of the bank. This is due to the compulsory conversion program, that required foreign currency-denominated household mortgage loans to be converted to forint-denominated loans. This policy successfully protect the household from the swiss franc shock and also change the banks net swiss franc asset position at the same time. Banks started to implement the conversions from February 2015, however, the conversion was effectively completed much earlier, as the exchange rate for conversion was fixed at the market rate on November 7th 2014. As a consequence, between these dates,

[13] This is due to regulatory requirements and the high demand for Swiss franc loans.

Swiss franc household loans, while considered local currency assets economically, were still recorded as foreign currency assets in accounting terms. Hence, when determining the pre-shock exposure measurement using 2014Q4 data, we need to subtract Swiss franc loans to households from Swiss franc assets. Formally, we express the *de facto* direct mismatch measurement for bank i as:

$$\text{DMismatch}_i^f = \frac{\text{CHF assets}_i - \text{CHF lending to households}_i - \text{CHF liabilities}_i}{\text{Total bank assets}_i} \tag{2.2}$$

It's important to highlight the significant efforts of the Central Bank of Hungary in managing the FX risks associated with the conversion program. They implemented measures, such as offering Forint/Euro swaps and advising commercial banks to use hedging instruments to mitigate other FX risks. However, commercial banks, driven by "cost-saving regulatory arbitrage" motivation, may reluctant in fully hedging. This motivation could be stranger when they expect that the forint would maintain its peg with the euro and the mismatches only in economic terms weren't within the regular regulatory scheme.

Indirect Mismatch

The indirect Swiss franc mismatch is quantified by considering Swiss franc lending to non-financial firms, which is part of banks' foreign currency-denominated assets. We measure the indirect Swiss franc mismatch for bank i as follows:

$$\text{IDMismatch}_i = \frac{\text{CHF lending to unhedged firms}_i}{\text{Total bank assets}_i} \tag{2.3}$$

$IDMismatch_i$ reflects the sensitivity of the bank's income to exchange rate fluctuations. Banks with higher Swiss franc lending to unhedged firms (standardized by bank assets) are expected to face greater credit losses following a Swiss franc appreciation. It's essential to understand that this measure should be viewed as the upper limit for Swiss franc mismatches, as we presume that all non-financial and non-exporting firms are incapable of hedging their Swiss franc liabilities against exchange rate risks.

We exclude Swiss franc loans to households from the calculation of indirect mismatch exposure due to the timely and effective conversion program and its pre-determined exchange rate, which insulate households from the exchange rate shock, preventing excessive defaults on household loans. Summary statistics and distribution plots for mismatch measurements, including alternative Swiss franc mismatch measurements used in our robustness checks, are provided in Appendices A.2 and A.3. Moreover, in Appendix A.4, we present supportive evidence showing that the exchange rate shock significantly affected firms' default rates. The data shows a marked increase in the average number of late payment days for CHF loans in 2015 compared to 2014, especially when compared to HUF and EUR loans.

3 Empirical framework and data description

3.1 Empirical framework

3.1.1 Loan-level bank lending channel

We utilize the fixed effect framework from Khwaja and Mian [2008] (2008) (hereafter KM framework) to identify post-shock credit supply effects at the loan level induced by the Swiss franc mismatch exposures on balance sheets. Consistent with the KM framework, we focus on firms with multiple forint-denominated bank lending relations and add fixed effects to control for firm-specific changes in credit demand. Therefore, the first-difference estimation can be expressed as follows:

$$gm(loans_{b,j}) = \beta_0 + \beta_1 DMismatch + \beta_2 IDMismatch + \Gamma X + \rho_j + \epsilon_{b,j} \tag{3.1}$$

Here, $gm(loans_{b,j})$ represents the normalized change in the size of a lending relation from bank b to firm j before and after the Swiss franc exchange rate shock. To avoid the omitted-variable bias, we simultaneously use both direct mismatch $DMismatch$ and indirect mismatch $IDMismatch$ as the dependent variables. Both measurements are obtained using the latest available quarterly data before the Swiss franc appreciation (2014Q4). X_b is a set of bank controls, and one crucial control variable is the banks' net Swiss franc swap-to-asset ratio, which can capture off-balance sheet losses induced by revaluation of swap contracts after the appreciation. ρ_j represents the firm fixed effect and can control for unobserved firm-specific changes in credit demand. This estimation is equivalent to a within-firm difference-in-difference approach. For the same firm, banks with a lower direct (indirect) mismatch before the Swiss franc appreciation serve as the control group for those with a higher direct (indirect) mismatch.

For our empirical analysis, we primarily focus our sample on firms engaged in multiple lending relationships with banks, exclusively involving loans denominated in forints. The rationale behind this choice is that these firms, lacking Swiss franc-denominated liabilities, are not directly affected by the Swiss franc exchange rate shock. This allows us to investigate the spillover effects of the exchange rate shock on borrowers who are not directly exposed.

Our analysis allows us to include a firm fixed effect, but only for firms that have multiple bank borrowing relationships. Without these fixed effects, a standard ordinary least squares (OLS) estimator could lead to biased estimates for the lending coefficient β_1, β_2 especially when measurements of currency mismatches correlate with changes in firm-specific credit demand that aren't directly observed Bottero et al. [2020]. For instance, consider a firm that operates in a region where many companies have Swiss franc debts. Following an appreciation of the Swiss franc, that region might experience economic downturns, thereby reducing the firm's credit demand[14]. This situation can create a negative correlation between firm-specific demand and direct mismatch. Conversely, if a firm is based in a region with a high concentration of exporters to Switzerland, an appreciation of the Swiss franc could increase these exporters' cash flow value and boost the local economy. This scenario can create a positive correlation between firm-specific demand and direct mismatch. Using an OLS estimator for the coefficient of the direct mismatch[15], the resulting expression, $\hat{\beta_1}^{OLS} = \beta + \frac{Cov(DMismatch_b, \rho_j)}{var(DMismatch_b)}$, suggests that in our analysis, $\hat{\beta_1}^{OLS}$ could either overestimate or underestimate the actual β_1. The KM framework mitigates this problem by comparing the growth of a single firm's loan from one bank to another more affected bank. We incorporate firm fixed effects to account for variations in firm-specific credit demand[16].

[14]Thanks to the successful conversion program, households were shielded. As a result, in our study, we can eliminate the confounding effects of the bank lending channel arising from household demand distress, enhancing our identification strategy.

[15]The same issue applies to the indirect mismatch; we are using the direct mismatch as an example here.

[16]which enables us to attribute the estimated change in loan growth following the exchange rate shock, $\hat{\beta_1}^{FE}$, to both the direct and indirect mismatches (derived from balance sheet items)

However, even with the inclusion of firm-specific fixed effects, biases may still arise if the shock is anticipated (Khwaja and Mian [2008], Bottero et al. [2020]). Under such circumstances, both banks and firms might adjust their loans beforehand, leading to either an under- or overestimation of the bank lending effect captured by $\hat{\beta_1}^{FE}$, depending on the strategic or precautionary adjustments made by the banks and firms. To address this concern, we focus on a specific event that occurred on January 15th, 2015, when Switzerland unexpectedly abandoned its 1.20 euro currency peg, triggering an immediate 20% surge in the Swiss franc. This event was widely reported as unanticipated [17]. This is further supported by the forward exchange rate on January 14th [18] which indicated that the market did not anticipate the event, and Switzerland's prior steadfast commitment to the euro [19]. Therefore, we consider this event to be exogenous and unforeseen for the Hungarian economy, allowing us to preclude any pre-emptive adjustments by banks and firms.

3.1.2 Firm-level corporate behaviour

After examining the impact of bank Swiss franc mismatches and the unexpected exchange rate shock on bank lending **at the loan level**, we proceed to analyze the results at the firm level. We focus on examining whether firms can mitigate the effects of credit supply variation from banks with higher exposure to mismatches by securing stable credit from other lenders and thereby maintain operational stability.

To estimate the impact of bank lending on corporations following the exchange rate shock, we must first determine the variation in credit supply at the firm level. Given that corporate borrowers are not be able to differentiate between credit supply variations caused by direct or indirect mismatches, they can only observe changes in credit supply at the bank level. Therefore, we begin by fitting the credit supply variation at the bank

[17] According to a Bloomberg survey of 22 economists conducted between January 9 and 14, 2015, none expected the Swiss National Bank (SNB) to abandon its minimum rate during the course of 2015, see: https://www.bloomberg.com/news/articles/2015-01-15/snb-unexpectedly-gives-up-cap-on-franc-lowers-deposit-rate

[18] Market forward rates from the day before the appreciation (overnight, 1 week, 1, 2, and 3 months) all stood at 1.2, indicating investor expectations of a stable exchange rate profile Auer et al. [2021]. Moreover, Jermann [2017] argue that option prices before January 15 revealed a low probability of abandoning the exchange rate floor.

[19] See: https://www.investopedia.com/articles/forex/013015/why-switzerland-scrapped-euro.asp

level using the results from our loan-level analysis[20]:

$$\Delta supply_b = \hat{\beta_1} DMismatch_b + \hat{\beta_2} IDMismatch_b \tag{3.2}$$

We calculate the firm-level credit supply variation by using the loan size-weighted average bank-level credit supply variation for each firm. Let $\mathbf{B}_j$ denote the set of all banks lending to firm j in 2014, and the firm j's weighted average exposure is calculated as follows:

$$\Delta supply_j^{AVE} = \sum_{b \in \mathbf{B}j} wbj \times \Delta supply_b \tag{3.3}$$

Here, w_{bj} represents the proportion of firm j's loans borrowed from bank b relative to the total credit extended to firm j by all banks in 2014, before the currency shock.

To estimate the effect of currency mismatch and exchange rate shock on firm behavior, we face the same identification challenges as in the loan-level regression. Specifically, we cannot include firm fixed effects, as we did in section (3.2), because the unit of observation is now a firm rather than a loan relationship (Schnabl [2012]). To address the identification issues when estimating firm-level activity, we add three sets of control variables that can help us capture firm-specific changes in credit demand. First, we include industry and region fixed effects. As argued in Bottero et al. [2020], industry-fixed effects can control for banks with high post-shock credit supply variation and specialize in industries prone to economic downturns. The region-fixed effect can control for the spatial clustering of banks and firms. Second, we add a set of firm controls that are important determinants of firm-specific variations in demand, measured in 2014. Third, we add the estimated firm fixed effect $\hat{\rho}_j$ from the loan-level analysis (3.2) as a control variable for the regressions where the dependent variable is firm-level activity. $\hat{\rho}_j$ is a vector of parameters charac-

[20] In the loan-level analysis, we report the coefficient of standardized independent variables (mismatch measurements), which is easier for interpretation. However, the fitted bank-level and firm-level credit supply variations are calculated based on the loan level regression without standardization since standardization could distort linear prediction from the fitted model.

terizing firm-specific credit demand (Cingano et al. [2016]). The estimated fixed effect can provide us useful information about the characteristics of firm-specific demand. Previous research shows that the estimated fixed effects from the KM framework correlate with variables that are related to credit demand, such as the expected investment rate (Cingano et al. [2016]; Bottero et al. [2020]).

We explore how various firm-level outcomes (y_j) are influenced by the Swiss franc mismatch in the bank's balance sheet using the following regression model:

$$y_j = \alpha_0 + \alpha_1 \Delta supply_j^{AVE} + \Gamma X_j^{AVE} + \Pi V_j + \rho^{industry} \times \rho^{region} + \hat{\rho}_j + \mu_j \tag{3.4}$$

In this model, $\Delta supply_j^{AVE}$ and X_j^{AVE} represent the loan-size weighted average variations in firm-level credit supply and bank-specific variables for firm j, respectively. V_j comprises a set of firm-level controls[21], measured in 2014. $\rho^{industry}$ and ρ^{region} refer to industry and province fixed effects, respectively. $\hat{\rho}_j$ denotes the estimated firm fixed effect. It's important to note that our firm-level regression uses generated regressors as independent variables. While coefficient estimates from generated regressors are generally consistent, their standard errors and t-statistics can be biased due to sampling errors associated with the generated regressors (Wooldridge [2002], Chen et al. [2023]). This bias arises because using generated regressors in second-step OLS regressions contradicts the standard OLS assumption. This assumption states that regressors are nonstochastic or known. This is not the case when we use a first-step auxiliary regression to create a regressor. This regression estimates coefficients, to create a predicted value. To correct this bias, we use the pairs cluster bootstrap method. Within each bootstrap cycle, we select a sample of firms and their associated loans, then conduct the first-step regression, fit the predicted value, and run the second-step regression. This method tackles the lack of sampling variation in the outputs of the first-step regression. This lack of variation is visible in the variation of the coefficient estimates from the second-step regressions. We use these estimates to calculate and report unbiased bootstrapped standard errors.

[21] The firm-level controls include log revenue, log size, employment, profit ratio, leverage, a dummy variable for foreign ownership, and age.

3.2 Data and summary statistics

Our analysis is based on several high-quality and detailed micro datasets. Our primary data source is the Hungarian Central Corporate Credit Registry, also known as "Központi Hitel Regiszter," which contains detailed quarterly credit information, such as the original credit amount, outstanding amount, maturity, and currency denomination for each contract. Our analysis focuses on loans denominated in Hungarian forint. To estimate the bank lending channel in Equation 3.1, we restrict our main sample to firms that obtained loans from at least two banks and only had Hungarian forint denominated loans both in 2014 and 2015.

For each quarters, we aggregate the amount of all contracts between the same bank and firm into a "loan," which we define as a bank-firm credit pair in our paper. The loan amount refers to the amount specified in the signed contract, not the actual outstanding due capital debt. We limit most of our analysis to a two-year period around the Swiss franc shock and further divide it into a pre-crisis period (from 2014:Q1 to 2014:Q4) and a post-crisis period (from 2015:Q1 to 2015:Q4). The primary dependent variable in our bank lending channel estimation is the loan growth rate, which measures the change in the size of a lending relation from bank b to firm j before and after the Swiss franc exchange rate shock. We calculate the loan growth rate using the following two steps. First, we collapse the quarterly loan amount between bank b and firm j into pre-shock and post-shock averages. Then we calculate the standardized growth rate between the pre- and post-shock averages (Chodorow-Reich [2014]):

$$gm(loan_{b,j}) = 2 \times \frac{loan_{b,j,post}^{average} - loan_{b,j,pre}^{average}}{loan_{b,j,post}^{average} + loan_{b,j,pre}^{average}}$$

The standardized growth rate $gm(loan_{b,j})$ represents a second-order approximation of the log difference growth rate around 0 and is bounded in the range $[-2, 2]$, which limits the influence of outliers and accounts for changes in credit along both the intensive and extensive margins. Furthermore, we also calculate a simple log growth rate ($g(loan_{b,j})$) between pre- and post-shock averages, which represents only the change along the intensive margin.

	Obs	Mean	Sd	Pc10	Pc90
Panel A : multi borrowing firm					
log HUF amount (2014)	9789	16.68	1.87	14.79	18.97
g(loan)	7953	0.01	0.84	-0.36	0.42
gm(loan)	10051	-0.26	0.94	-2.00	0.49
Panel B : multi and single borrowing firm					
log HUF amount (2014)	44790	16.25	1.80	14.22	18.43
g(loan)	39124	0.02	0.59	-0.32	0.41
gm(loan)	52504	0.10	1.05	-2.00	2.00

This table presents summary statistics for the loan-level variables used in the empirical analysis. Panel A reports loans for firms that obtained Hungarian forint denominated loans from at least two banks in 2014. Panel B reports loans for all firms that obtained Hungarian forint denominated loans from banks. The variable g(loan), which measures the log growth rate, excludes observations for firm-bank pairs with zero loan amount either in 2014 or 2015, and represents changes along the intensive margin. The variable gm(loan), which measures the standardized growth rate, includes more observations than g(loan) as it accounts for changes in credit along both the intensive and extensive margins, and includes firm-bank pairs with zero loan amount either in 2014 or 2015.

Table 1: Summary statistic loan

Table 1 presents the summary statistics for the variables at the loan level, which refer to the relationship between a bank and a firm. The primary sample used in our analysis comprises firms that have obtained Hungarian forint denominated loans from multiple banks. The loans given to these firms have, on average, a larger amount denominated in forints compared to the loans given to all firms. Moreover, loans extended to multibank firms exhibit a lower standardized growth rate from 2014 to 2015.

To examine the effects of the bank-lending channel on firms, we link the data from the Corporate Credit Registry to the corporate tax filings of the National Tax and Customs Administration, which provide information on the financial statements, industry, location, and age of all double-entry bookkeeping firms in Hungary. By doing this, we obtain a sample of 45,143 non-financial firms that only had loans denominated in Hungarian forint and were active in 2014, out of which 4,606 firms obtained loans from multiple banks. Table 2 presents summary statistics for key firm-level variables before the shock (2014). On average, multibank firms are larger, have higher revenue, and employ more people.

The final step of our data preparation involves matching the Corporate Credit Registry

	Obs	Mean	Sd	Pc10	Pc90
Panel A : multifirm					
Log revenue	4522	12.16	1.72	10.13	14.27
Log size	4575	11.89	1.73	9.94	14.13
Employment	4496	34.86	218.55	2.00	50.00
Profit to balance sheet ratio	4575	-0.08	7.52	-0.01	0.19
Leverage	4575	3.70	187.09	0.26	0.88
Foreign ownership	4606	0.02	0.15	0.00	0.00
Age	4606	15.81	6.96	7.00	25.00
Annual real total capital growth	4361	0.03	0.65	-0.29	0.44
Panel B : multi and single firm					
Log revenue	43699	11.26	1.76	9.15	13.42
Log size	44950	10.90	1.79	8.84	13.17
Employment	42478	15.87	103.21	1.00	25.00
Profit to balance sheet ratio	44950	-0.53	38.42	-0.07	0.27
Leverage	44950	6.37	414.11	0.18	0.95
Foreign ownership	45143	0.03	0.17	0.00	0.00
Age	45142	13.64	7.17	5.00	24.00
Annual real total capital growth	42511	0.10	1.05	-0.39	0.76

This table provides summary statistics for the firm-level variables used in the empirical analysis. Panel A reports summary statistics for firms that obtained loans denominated in Hungarian forint from at least two banks. Panel B reports summary statistics for all firms that obtained loans denominated in Hungarian forint from banks during 2014-2015.

Table 2: Summary statistic firm

data with the Central Bank of Hungary's supervisory records on the quarterly bank balance sheets. This matching process enables us to calculate the exchange rate exposure of each bank in 2014:Q4. Our original sample of bank balance sheets data includes 105 financial intermediaries (banks and saving cooperatives), which had corporate loans in 2014. We have excluded 16 because of merger or closure during 2015-2017 and a further 45 saving cooperatives that did not have at least 1% CHF asset in their balance sheet. We limit our sample to the 23 commercial banks operating in national level and 21 big local saving institutions covering 90 % of the corporate loan amount in 2014Q4.Appendix A.5 provides summary statistics for the primary bank-level variables used as controls in our analysis. It is worth noting that we standardize all bank-level variables, firm-level variables, and mismatch measurements in our empirical analysis. The summary statistics tables report the values without standardization.

4 The bank lending channel

4.1 The bank lending channel: main results

	(1)	(2)	(3)	(4)
	FE	OLS	OLS	FE
	gm(loan)	gm(loan)	gm(loan)	gm(loan)
$DMismatch^f$	0.190***	0.116***	0.115***	
	(0.039)	(0.032)	(0.018)	
$DMismatch^j$				0.033
				(0.074)
IDMismatch	-0.098***	-0.060***	-0.037***	-0.105***
	(0.022)	(0.015)	(0.007)	(0.034)
Bank Controls	Yes	Yes	Yes	Yes
R^2	0.398	0.013	0.336	0.394
Number of observations	10,052	10,052	52,790	10,052
Firm fixed effect	Yes	No	No	Yes
Bank type	Bank	Bank	Bank	Bank
Firm borrowing type	Multiple	Multiple	Multiple&Single	Multiple

This table presents an analysis of the transmission of the exchange rate shock to credit supply through the bank lending channel. The dependent variable is the normalized growth rate in loans, gm(loan), granted by bank b to firm j between the pre-crisis period (from 2014:Q1 to 2014:Q4) and the post-crisis period (from 2015:Q1 to 2015:Q4). The primary independent variables are the direct and indirect exposures of banks to Swiss franc mismatches measured in 2014:Q4. All columns include a set of bank controls, including (1) the loan-to-risk-weighted assets ratio, (2) the loan-to-deposit ratio, (3) a dummy variable for low tier one capital, (4) the capital adequacy ratio, (5) the loan loss provision to risk-weighted assets ratio, (6) the total deposits to liability ratio, (7) the return on assets, (8) the liquidity to risk-weighted assets ratio, (9) the interbank deposits in liabilities to risk-weighted assets ratio, and (10) the CHF swap to risk-weighted assets ratio. Models in Columns 1 and 4 are estimated on a sample of firms with multiple lending relationships and include firm fixed effects. Column 4 includes an additional variable, CHF household loan to total asset ratio, to control for the potential impact from CHF household loans. The model in Column 3 includes both single- and multiple-relationship firms. Standard errors are clustered at the bank level. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 3: The bank lending channel:main results

Table 3 presents our baseline estimation results, which examine the impact of *de facto* direct and indirect mismatches on credit supply to firms following the Swiss franc appreciation. Column (1) reports the results using the KM framework (FE estimation) specified in Equation 3.1, which provides an unbiased estimate of the bank lending channel coefficient (Khwaja and Mian [2008]). We limit the sample to firms with forint denominated loans from multiple banks.

The estimated coefficient of *de facto* direct mismatch is positive and statistically significant at the 1% level. This suggests that the net Swiss franc asset position before the exchange rate shock is positively related to post-shock credit supply. Specifically, for two banks with a similar amount of Swiss franc liabilities, the bank with more Swiss franc assets experienced a higher loan growth in the post-shock period than those with fewer Swiss franc assets, after controlling for firm-specific demand[22]. Quantitatively, we find that when comparing lending to the same firm by two banks that are one standard deviation apart in terms of net Swiss franc asset position, the lender with a higher position increases credit by about 19%[23] more than the lender with a lower position. The significant coefficient of the *de facto* direct mismatch underscores that banks do not perfectly hedge the mismatch between their Swiss franc assets and liabilities. This aligns with our prior section detailing how commercial banks might be reluctant to perfectly hedge, due in part to inaccurate predictions of the shock and their tendencies towards "cost-saving regulatory arbitrage" behavior. [24]. The estimated coefficient of IDMismatch reveals a clear contractionary impact of the indirect mismatch on post-shock bank lending. Specifically, an increase in exposure to indirect Swiss franc mismatch risk by one standard deviation predicts a drop of about 9.8% in credit supply after controlling for firm-specific demand. This finding suggests that foreign currency borrowers transmit significant exchange rate risk to bank balance sheets through the credit loss of Swiss-franc-denominated corporate loans and further spillover to local currency borrowers.

Column (2) of Table 3 presents our estimation results using a simple OLS model, where we exclude firm fixed effects and examine the impact of Swiss franc mismatches on the bank lending channel. We use the same sample as in column (1). The estimated co-

[22] This finding is consistent with previous studies, such as Agarwal [2018], which also examined the impact of the currency appreciation shock from Switzerland in January 2015 and found that it enabled Swiss banks with net foreign currency liability exposure to increase their credit supply

[23] All mismatch measurements are standardized.

[24] This finding is consistent with closely related studies (Abbassi and Bräuning [2021] and Beck et al. [2022]). As previously discussed, while banks can stabilize exchange rates of net position using forward derivative contracts, these can be costly. Banks' imperfect hedging from two main reasons: first, as Agarwal [2018] points out, banks' risk assessments based on historical data might not foresee future dynamics. In our case, this can lead to underestimating exchange risks due to past Euro-Swiss franc pegging, particularly when aided by the Central Bank of Hungary's Euro/Forint swaps. Second, the cost of collateral requirement for hedging can strain banks, prompting some to reduce or postpone hedging until regulatory filings Puriya and Bräuning [2021].

efficients of both *de facto* direct mismatch and IDMismatch have the same signs as in the fixed effect regression, but they show declines in significant level and absolute value. This finding suggests that the OLS estimation underestimates the impact of both mismatches compared to the fixed effect estimation.

The results of fixed effect and OLS estimations consistently demonstrate the significant impacts of pre-shock net Swiss franc asset position (direct mismatch) and lending to unhedged borrowers (indirect mismatch) on the post-shock bank supply of forint-denominated credit. These impacts are not limited to firms with multiple lending relationships. To further explore this, column (3) presents the OLS estimation results for a sample of all firms borrowing from banks in 2014, including both single- and multiple-borrowing. The two mismatch risk exposure coefficients are statistically significant at the 1% level. Considering the previous discussion in columns (1) and (2) which suggests OLS estimation results could underestimate, the OLS estimation on the sample with all firms confirms that the bank lending channel also existed for single-relationship firms.

When we compare the *de facto* and *de jure* measures of direct mismatch (column 4), we find that the latter yields an insignificant coefficient. This result suggests that the *de facto* measure is a more precise measure of the actual net Swiss franc asset position, which takes into account adjustments for Swiss franc household loans. Our results suggest that the impact of the Swiss franc appreciation on credit supply varies across banks, depending on their balance sheet structures, including their net Swiss franc asset positions and the amount of lending to unhedged borrowers. Understanding these heterogeneous effects is crucial for regulators, who need to assess the potential risks associated with foreign currency borrowing and lending. Our results shed light on the bank lending channel and highlights the importance of taking into account bank balance sheet structures when assessing the impact of exchange rate shocks on credit supply. Figure 3 depicts the fitted credit supply variations at the bank level based on each bank's net Swiss franc asset position and the amount of lending to unhedged firms. To minimize the bias of the fitted credit variation, we added the interest rate compensation control in the loan-level regression. We will discuss this control in the next subsection. The figure highlights the heterogeneity in the impact of Swiss franc appreciation on bank-level credit supply. The impact is contractionary for most banks, with only banks having large positive net asset positions showing an expansionary effect.

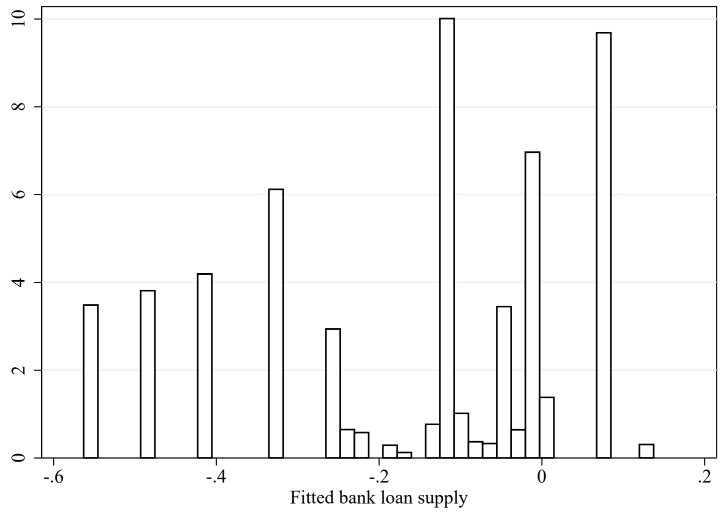


Figure 3: fitted bank-level credit supply effect

This figure shows the variation in fitted bank-level credit supply based on loan-level regressions with non-standardized independent variables. To control for omitted variables, we include interest rate compensation as a control variable in the bank lending regression.

Our analysis centers on the influence of two on-balance sheet mismatches on bank lending, while considering the net Swiss franc swap position as a control for potential off-balance sheet mismatch effects. This approach allows us to account for potential impacts on credit supply resulting from changes in swap costs and margin requirements after the Swiss franc appreciation. In Appendix A.6, we briefly discuss the effects of off-balance sheet mismatches and report the results. Column (1) presents the estimate of the coefficient for the net Swiss franc swap position, using the specifications from equation 3.1. We find that the coefficient is positive and statistically significant, even after accounting for changes in demand conditions at the firm level. This result suggests that the off-balance sheet net Swiss franc asset position (swap position) impacts bank lending similarly to the on-balance sheet net Swiss asset position: Swiss franc appreciation enables banks with net positive off-balance sheet asset exposure to increase their credit supply. The significant coefficients of both net Swiss franc asset positions also suggest the on and off-balance sheet items do not perfectly hedge each other. We briefly discuss the combined impact of on and off-balance sheet mismatches on post-shock credit supply in Appendix A.6.

4.2 The bank lending channel: Robustness tests

The results in table 3 reveal a linkage between two mismatches on bank balance sheets and the variation of credit at the onset of the Swiss franc appreciation. In this section, we proceed to address a number of concerns related to the robustness of our baseline results.

Alternative explanations

	(1) FE gm(loan)	(2) OLS gm(loan)	(3) FE gm(loan)	(4) OLS gm(loan)
DMismatch^f	0.197***	0.117***	0.293***	0.132***
	(0.045)	(0.015)	(0.053)	(0.023)
IDMismatch	-0.087***	-0.034***	-0.088***	-0.041***
	(0.026)	(0.008)	(0.021)	(0.008)
Bank Controls	Yes	Yes	Yes	Yes
Interest rate compensation	No	No	Yes	Yes
R^2	0.400	0.378	0.398	0.337
Number of observations	8,900	46,406	10,052	52,790
Firm fixed effect	Yes	No	Yes	No
Bank type	Bank	Bank	Bank	Bank
Firm borrowing type	Multiple	Multiple&Single	Multiple	Multiple&Single
Drop top 10% size firm	Yes	Yes	No	No

This table presents robustness tests for alternative explanations. The dependent variable is the normalized growth rate in loans, gm(loan), granted by bank b to firm j between the pre-crisis period (from 2014:Q1 to 2014:Q4) and the post-crisis period (from 2015:Q1 to 2015:Q4). The main independent variables are bank direct and indirect exposures to Swiss franc mismatches measured in 2014:Q4. All columns include a set of bank controls, which are: (1) loan to RWA ratio, (2) loan to deposit ratio, (3) low tier one capital dummy, (4) capital adequacy ratio, (5) loan loss provision to RWA ratio, (6) total deposits to liability ratio, (7) return on assets, (8) liquidity to RWA ratio, (9) inter-bank deposits in liabilities to RWA ratio, and (10) CHF swap to RWA ratio. The models in columns 1 and 3 are estimated on the sample of firms with multiple lending relationships and include firm fixed effects. The model in columns 2 and 4 includes both single- and multiple-relationship firms. Standard errors are clustered at the bank level. Columns 1 and 2 exclude the top 10% largest firms by size, while columns 3 and 4 include interest penalty as a control variable. Significance levels are denoted as *** for 1%, ** for 5%, and * for 10%.

Table 4: The bank lending channel: Robustness tests for alternative explanations

The results presented in Table 3 suggest a link between the two mismatches on bank balance sheets and the credit variation observed during the Swiss franc appreciation. However, to ensure the robustness of these findings, we address several concerns in this section.

One potential concern with our identification strategy is that our baseline results could be partially driven by other market funding conditions, such as bonds or equity. This is because firms that issue more or less external debt in the funding market may change their loan demand following the Swiss franc appreciation, and this demand change may coincide with the pre-shock bank exposures to Swiss franc mismatch risk exposures. To test this concern, we exclude the top 10% of firms in size[25] in each sample and check whether our baseline results change. We should expect the coefficients to remain unchanged if our baseline results are not driven by market funding because only large firms in an economy can access the bond or equity market[26]. The results, presented in Columns (1) and (2) of Table 4, show that the coefficients are almost the same as those in Table 3. This suggests that firms' market funding behavior did not drive the main results from the baseline specification.

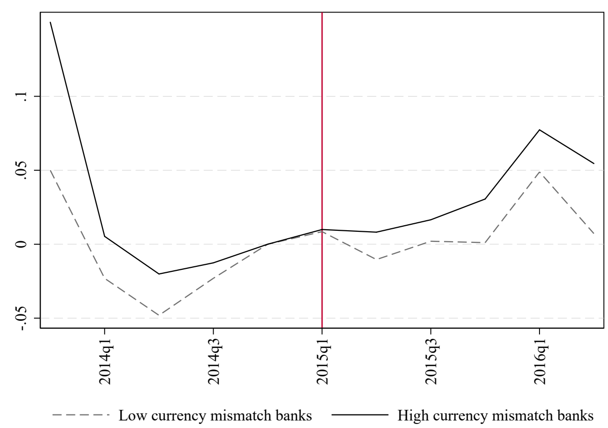
There was a policy event that coincided with the exchange rate shock and may have had a negative impact on the loan growth of banks with low net asset exposure to the Swiss franc. In conjunction with the conversion program, the Hungarian government regulated the interest rates of converted foreign currency mortgage loans and requested that banks compensate household borrowers for the excess interest charged in the past. This policy can be viewed as an interest rate "compensation" from the banks' perspective, as it results in additional losses for bank operations, which could lead to a reduction in credit supply thereafter. To account for the impact of this specific policy, we calculated the interest rate compensation amount at the bank level and included it in our baseline regression. The addition of this control had no on the q coefficients, as evidenced by columns (3) and (4) in Table 4.

Another possible concern regarding our identification strategy is that pre-existing trends may be driving the difference in post-shock lending growth between banks with high versus low Swiss franc mismatch risk. To address this concern, we check for parallel trends

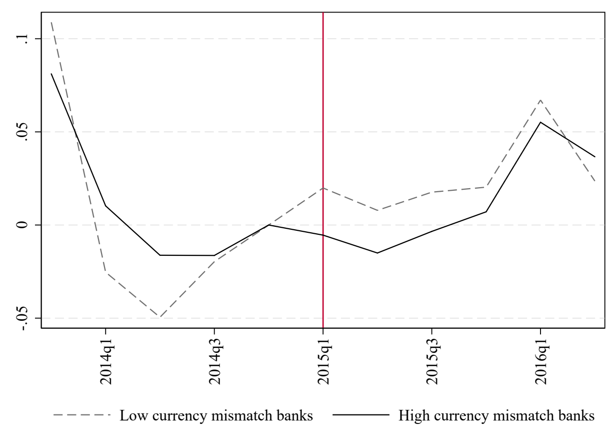
[25]Firm size is proxied by total assets.

[26]Although the percentage of firms that can access market funding is much less than 10%, we set the criterion as 10% considering our sample of firms with multiple-lending relationships are larger on average. During the analyzed period, it was not prevalent among Hungarian corporations to issue bonds, apart from a few banks.

at the aggregate level. To do so, we follow the method proposed by Bottero et al. (2020) to semi-parametrically sort banks in our final sample into ”High” and ”Low” groups based on their (conditional) de facto direct and indirect currency mismatch in the last quarter of 2014, which was just before the CHF shock occurred on January 15, 2015. The two groups in each sorting can be considered as ”treatment” and ”control” groups[27]. We then aggregate the loan stock volumes provided by banks in the High and Low mismatch exposure groups separately for each sorting. Finally, we plot the log values of the two time series by normalizing each on the y-axis to 0 in 2014Q4.



(a) Sorting by *de facto* direct mismatch



(b) Sorting by indirect mismatch

Figure 4: The bank lending channel at aggregate level

This figure depicts a semi-parametric illustration of the bank lending channel by comparing lending to firms from banks sorted by their *de facto* mismatch (on the left) and indirect mismatch (on the right).

Figure 4 illustrates bank lending channel by comparing lending to firms from banks sorted by their *de facto* direct mismatch (graph 4a) and indirect mismatch (graph 4b). The y-axis value shows the log growth rates in nominal lending in each quarter relative to the lending in 2014Q4. Both graphs include loans received by single-bank and multi-bank borrowing firms. The bank lending trends at the aggregate level in Figure 4 provide support for our identification strategy. Observing the left part of Figure 4 there was no

[27] To sort the banks, we run a cross-sectional regression of the bank-level mismatch measurements on the same bank characteristic controls used in the rest of our analysis, all measured in 2014Q4. Based on the estimated residuals of the regression, we assign banks to the ”High mismatch” group if their residuals are above the median and to the ”Low currency mismatch” group if their residuals are below the median. This way, we can classify banks based on the cross-sectional variation of their exposure to currency mismatch that is not attributed to bank-specific characteristics.

difference in the trend of aggregate credit supply before the shock between banks with high and low Swiss franc mismatch exposure. Based on the figure on the right it is, however, less obvious that trends were differing before the shock. Based on the evidence on figure left, we conclude that there is some evidence that the divergence in trends right after the Swiss franc appreciation cannot be attributed to preexisting differential trends.

To provide quantitative support for no difference in trend prior to the shock, we follow Schnabl [2012] to estimate a placebo regression using data two years before the Swiss franc appreciation shock. The specification of the placebo regression is the same as our baseline regression for loan-level analysis[28]. Table 5 presents the results of the placebo test. These results indicate no significant differential trends by direct and indirect currency mismatch exposure in the two years before the Swiss franc shock.

	(1) FE gm(loan)	(2) OLS gm(loan)
DMismatch^f	-0.027	-0.001
	(0.039)	(0.031)
IDMismatch	-0.017	0.004
	(0.041)	(0.029)
Bank Controls	Yes	Yes
R^2	0.429	0.015
Number of observations	9,154	9,154
Firm fixed effect	Yes	No
Bank type	Bank	Bank
Firm borrowing type	Multiple	Multiple

The regressions in this table examine the impact of currency mismatch exposures on bank lending in the 2-year period before the Swiss franc appreciation. The specification is same as 3.1. The outcome variable is the normalized growth rate in loans ($gm(loan)$) granted by bank b to firm j between the pre-crisis period (from 2012:Q1 to 2012:Q4) and the post-crisis period (from 2013:Q1 to 2013:Q4). All columns include a set of bank controls that are the same as those used in the baseline regression. We also include the interest rate "compensation" as control variable. Standard errors are clustered at the bank level. The notation $***$ indicates statistical significance at the 1% level, $**$ indicates significance at the 5% level, and $*$ indicates significance at the 10% level.

Table 5: The bank lending channel:placebo test

[28]We also include the interest rate penalty in the placebo test for controlling the possible expectation effect, which could be feedback to the credit supply two years ago. And this is the only control variable in the placebo test from 2014Q4.

Alternative outcome variables

To ensure the robustness of our results, we conducted several additional tests on alternative outcome variables. In table 6, we present the results of these tests. We first examined the relationship between the "exit rate" of a bank-firm lending relationship and direct and indirect mismatches in columns (1) and (2). The "exit" dummy variable equals one when a credit relationship established before the shock is terminated in the post-shock period. In the fixed effects (FE) specification, we found that banks with higher indirect mismatch exposure were more likely to terminate a credit relationship, leading to a 4% increase in the probability of exit for a one-standard-deviation increase in indirect mismatch exposure. However, this impact was not significant in the ordinary least squares (OLS) estimation that included all firms. We also found that higher net Swiss franc asset positions reduced the exit rate, as indicated by the significant and negative coefficients of direct mismatch exposure in both specifications, which is consistent with our main results. We further examined effects along the intensive margin in columns (3) and (4). The dependent variable is the simple log growth rate of the amount of credit granted to firm j by bank b between the pre-shock average (2014:Q1-2014:Q4) and the post-shock average (2015:Q1-2015:Q4)[29]. We found that both direct and indirect mismatches had significant effects on credit supply through both intensive and extensive margins, which were similar in magnitude to our main results. Taken together, columns (1) to (4) confirmed our main results and provided additional evidence that direct and indirect mismatches affect credit supply through both intensive and extensive margins.

Alternative measurement and alternative specification

To test whether our results are sensitive to the definition of currency mismatch variable, we construct an alternative measure of Swiss franc mismatch exposure. In particular, we adopt the systemic currency mismatch measurement proposed by Ranciere et al. [2010], which captures both direct and indirect currency mismatch risk at the country level. This measurement excludes foreign currency loans to unhedged borrowers from foreign currency assets when calculating net foreign currency liabilities position. The intuition be-

[29]When conducting a regression with the Log growth rate, we omit observations that have a value of zero. This exclusion ensures that we capture only the intensive margin effect.

	(1)	(2)	(3)	(4)
	FE	OLS	FE	OLS
	Exit	Exit	g(loan)	g(loan)
DMismatch^f	-0.040***	-0.031***	0.144***	0.101***
	(0.014)	(0.005)	(0.027)	(0.019)
IDMismatch	0.040***	0.002	-0.063***	-0.102***
	(0.008)	(0.003)	(0.015)	(0.018)
Bank Controls	Yes	Yes	Yes	Yes
R^2	0.469	0.009	0.463	0.031
Number of observations	10,052	52,790	6,602	39,328
Firm fixed effect	Yes	No	Yes	No
Bank type	Bank	Bank	Bank	Bank
Firm borrowing type	Multiple	Multiple&Single	Multiple	Multiple&Single

This table presents several robustness tests for alternative outcome variables. The outcome variable is the "Exit" dummy in columns 3 and 4 and the simple log growth rate in columns 5 and 6. The primary independent variables are bank direct and indirect exposures to Swiss franc mismatches measured in 2014Q4. All columns include a set of bank controls, which are (1) loan-to-RWA ratio, (2) loan-to-deposit ratio, (3) low tier one capital dummy, (4) capital adequacy ratio, (5) loan loss provision to RWA ratio, (6) total deposits to liability ratio, (7) return on assets, (8) liquidity to RWA ratio, (9) inter-bank deposits in liabilities to RWA ratio, and (10) CHF swap to RWA ratio. Standard errors are clustered at the bank level. *** denotes significance at the 1% level, ** at the 5%, and * at the 10%.

Table 6: The bank lending channel:Robustness tests

hind this measurement is similar to our own measures. [30] Specifically, we construct a bank-level "systemic" Swiss franc mismatch exposure as follows:

$$\text{SMismatch}_i = \frac{\text{CHF assets}_i - \text{CHF liabilities}_i}{\text{Total bank assets}_i}$$

$$- \frac{\text{CHF lending to unhedged firms}_i}{\text{Total bank assets}_i} - \frac{\text{CHF lending to Households}_i}{\text{Total bank assets}_i}$$

We estimated the KM framework using this alternative measure. If our baseline results are consistent with the systemic mismatch measure, we should observe a positive coefficient. Because systemic mismatch comprises two components: the direct mismatch and

[30] Ranciere et al. [2010] considers lending to unhedged borrowers as part of the systemic mismatch risk, as depreciation of the domestic currency can increase the debt burden with contractionary consequences for unhedged borrowers. In our analysis, we construct the systemic mismatch risk measure as the sum of net foreign currency liabilities and lending to unhedged borrowers for each bank.

the negated indirect mismatch. Both components have a positive correlation with credit supply. We report the results in table A.7, column (1). The coefficient estimated from the KM framework is positive and significant at the 1% level. This result is consistent with the implication of our baseline result. In terms of economic magnitude, a one-standard-deviation increase in the systemic Swiss franc mismatch exposure predicts a step-down in credit supply of about 20.5% after controlling for firm-specific demand. We also report the test of the parallel trends assumption at the aggregate level for the systemic mismatch exposure in the appendix.

In Appendix A.8, we further address potential concerns about the construction of our primary dependent variables. To test whether our results are influenced by certain banks also operating as investment banks, we first construct a direct mismatch measure which includes Swiss franc market securities in asset side in column (1). In column (2), we exclude Swiss franc lending to foreign-owned firms from our indirect mismatch measure to account for potential appreciation responses from other economies. In column (3), we exclude Swiss franc provisions from liabilities when constructing direct mismatches. All three columns indicate that our estimation results maintain both qualitative and quantitative robustness when employing alternative constructions of the dependent variables.

In Appendix A.9, we conduct a robustness check of our main findings using an alternative model. This model is designed to capture the quarterly fluctuations in loan volume around the period of Swiss franc appreciation. The equation for this regression is:

$$\begin{aligned} log(loan)_{b,j,t} =& \beta_0 + \beta_1 DMismatch_{b,2014Q4} * Post + \beta_2 IMismatch_{b,2014Q4} * Post + \\ &+ Post + \Gamma X_{b,2014} + \Pi V_{j,2014} + \rho_j + \rho_j^{industry} + \rho_j^{region} + \rho^{time} + \epsilon_{b,j,t} \end{aligned}$$

Here, the dependent variable is the logarithm of loan volume between bank b and firm j in each quarter t during the time period of 2014-2015. The primary independent variables are interaction terms between the post-shock period and mismatch exposures. Alongside the firm fixed effect, we introduce a collection of control variables - including firm characteristics, industry, time, and regional fixed effects - to account for firm-specific credit demand changes[31]. This model allows us to identify the quarterly variations in loan growth and lends further robustness to our primary findings. The estimated effects of direct and indirect Swiss franc mismatch exposures remain positive and negative, respectively. This specification provides additional support to our assertion, indicating that our findings are not solely influenced by using growth rate as a measure for credit supply variation.

4.3 The bank lending channel: the transmission mechanism

We now examine the transmission channels that could explain the post-shock variation in bank credit supply resulting from the exchange rate shock and pre-shock mismatch exposures on balance sheets. As we outlined in hypothesis development: (1) banks with net Swiss franc asset positions see a immediate revaluation, resulting in an increase in capital and liquidity[32] which shape the bank's lending capacity. (2) banks with a higher volume of Swiss franc lending to unhedged firms will experience greater credit losses after the Swiss franc appreciation. This results in a reduction in their liquidity position and capital buffer, leading to a decrease in credit supply. Therefore, given the appreciation of the Swiss franc, we hypothesize transmission to the credit supply via the capital and liquidity channels. Specifically, after the shock, banks are expected to see shifts in their capital constraints. Simultaneously, those with limited liquidity may exhibit higher marginal credit supply growth than banks with abundent liquidity.

To assess the capital channel, we examine the relationship between banks' changes in capital adequacy ratio around shock and two mismatch measurements. We employ two regression approaches. In the first, we conduct bank-level regressions, each weighted by the respective bank's total assets. The second approach comprises loan-level regressions, maintaining the firm fixed effect specification previously utilized in our loan-level analysis. This is can be economically interpreted as a loan number-weighted regression[33]. Our dependent variables capture the shifts in the capital adequacy ratio from 2014Q4 to 2015Q1, and from 2014Q4 to 2015Q2, show in odd and even columns, respectively.

[31] The control variables are akin to the variables used for firm-level impact analysis in the subsequent section

[32] Extra cash flow generate liquidity when asset or liability are in short maturity

[33] This specification, having the change in the capital adequacy ratio as the dependent variable, can be perceived as the first stage of our loan-level bank lending regression. Alterations in the capital adequacy ratio, as a consequence of currency mismatch, could subsequently impact loan growth

	(1)	(2)	(3)	(4)
	WLS	WLS	FE	FE
	ΔCAR_{2015Q1}	ΔCAR_{2015Q2}	ΔCAR_{2015Q1}	ΔCAR_{2015Q2}
DMismatch^f	0.843**	0.762*	1.000***	0.761**
	((0.348)	(0.406)	(0.238)	(0.360)
IDMismatch	-0.597*	-0.406	-0.627***	-0.634**
	(0.309)	(0.360)	(0.167)	(0.250)
Bank Controls	Yes	Yes	Yes	Yes
R^2	0.856	0.892	0.936	0.938
Number of observations	44	44	10,052	10,052
Firm fixed effect	No	No	Yes	Yes

This table presents test results for the direct relationship between mismatches and changes in the capital adequacy ratio. The dependent variables are the changes in the capital adequacy ratio between 2014Q4 and 2015Q1, or between 2014Q4 and 2015Q2. The primary independent variables are the bank's direct and indirect exposures to Swiss franc mismatches as measured in 2014Q4. All columns include a set of bank controls, specifically: (1) loan-to-RWA ratio, (2) loan-to-deposit ratio, (3) low tier one capital dummy, (4) loan loss provision to RWA ratio, (5) total deposits to liability ratio, (6) return on assets, (7) liquidity to RWA ratio, (8) inter-bank deposits in liabilities to RWA ratio, and (9) CHF swap to RWA ratio. Columns (1) and (3) utilize the changes in the capital adequacy ratio between 2014Q4 and 2015Q1 as the dependent variable. Columns (2) and (4) use the changes in the capital adequacy ratio between 2014Q4 and 2015Q2 as the dependent variable. The regression models for Columns (1) and (2) employ bank asset-weighted least squares and use bank-level data. The regression models for Columns (3) and (4) incorporate a firm fixed effect, consistent with the loan-level bank lending analysis, and use loan-level data. The significance levels are denoted as follows: *** indicates significance at the 1% level, ** at the 5

Table 7: Link between mismatches and capital adequacy ratio change

Table 7 presents the test results for the direct link between mismatches and changes in the capital ratio. From columns (1) and (3), we find that the direct mismatch is positively significant with the change in the capital adequacy ratio from 2014Q4 to 2015Q1, while the indirect mismatch is negative and economically significant with respect to the change in the capital adequacy ratio. When compared to the change in the capital adequacy ratio between 2014Q4 and 2015Q2, the correlation is particularly strong in the quarter when the Swiss franc appreciation shock occurred. These results provide direct evidence that net worth can be influenced by two on-balance-sheet Swiss franc mismatches, which are likely to further influence credit supply through capital constraints or liquidity.

To explore the transmission channels, we incorporated interaction terms between exposures and a dummy variable representing a low liquidity ratio[34]. To achieve balance in

[34]While the tables display the interaction terms, every regression also includes the associated non-interacted variable.

each group, the dummy is assigned a value of one if the liquidity ratio exceeds the median value, which is calculated based on the total number of loans. From the entire set of 10,052 observations, we calculate the median bank liquidity ratio at the loan level. We divide the data into two subgroup, each comprising 5,026 observations. This division implies that half the loans are sourced from high liquidity banks, with the remaining half from banks with lower liquidity. Table 8 presents our findings. It's evident that firms borrowing from banks with lower liquidity ratios (seen in Column 1) experience a more pronounced effect of net Swiss franc asset revaluation on credit supply than those borrowing from banks with a higher liquidity ratio. When we consider the interaction term related to exposure to Swiss franc corporate lending, it becomes clear that firms borrowing from banks with lower liquidity ratios face a larger drop in credit supply in 2015 (as shown in Column 4). These observations support the idea that the liquidity channel influences the translation of exchange rate changes to credit supply.

5 The firm level impact of the bank lending channel

Our results in previous sections based on loan-level data point to significant variation in bank lending during the post-shock period, which was caused by the two types of Swiss franc mismatch exposures on banks' balance sheets. However, loan level results does not give us a complete picture of the net firm-level effect of bank lending channel, because individual firms affected by some banks may set up new borrowing relation with other banks to seek financing to compensate for any loss of credit (Jiménez et al. [2020]). In this section, we examine the impact of credit supply changes on firms. We are particularly interested in answering two questions: (1) Can firms offset the bank-specific loan supply variation by setting up new borrowing relation with other banks with lower pre-shock Swiss franc mismatch exposures? (2) How do changes in loan supply affect firm operations?

We investigate the impact on firms by using two samples - one with firms borrowing from multiple banks and the other with all firms, where both samples only include firms borrowing Hungarian forint loans. As discussed in section 3.3.2, using multi-borrowing firms has the advantage of allowing us to add the estimated firm fixed effect $\hat{\rho}_j$ from the loan level analysis to control for the firms' specific demand. Our baseline results on

	(1)	(3)
	FE	FE
	gm(loan)	gm(loan)
DMismatch^f	-0.044	0.276***
	(0.159)	(0.043)
IDMismatch	-0.157***	0.005
	(0.022)	(0.072)
DMismatch^f Interacted with		
low liquidity ratio dummy	0.349*	
	(0.189)	
IDMismatch Interacted with		
low liquidity ratio dummy		-0.165**
		(0.074)
Bank Controls	Yes	Yes
R^2	0.401	0.401
Number of observations	10,052	10,052
Firm Fixed effect	Yes	Yes
Bank type	Bank	Bank
Firm borrowing type	Multiple	Multiple

To investigate the transmission channels of direct and indirect Swiss franc mismatch exposures through banks' balance sheets, we modified regression equation 3.1 and examined one interaction of low liquidity ratio dummy with a mismatch exposure at a time. In this regression, the dummy variables that take a value of one if the observation was low than the median for bank liquidity ration in loan level. The dependent variable is the normalized growth rate in loans (gm(loan)) granted by bank b to firm j between the pre-crisis period (from 2014:Q1 to 2014:Q4) and the post-crisis period (from 2015:Q1 to 2015:Q4). All columns include the same set of control variables as the baseline regression. We estimated the model using within-firm estimates on the sample of firms with multiple lending relationships and included firm fixed effects. Standard errors are clustered at the bank level. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 8: channels of transmission

the bank lending channel show that the actual credit supply effects at the bank-level are heterogeneous, and we assume that corporate borrowers cannot distinguish the credit supply variation induced by direct or indirect mismatch. Therefore, we construct the firm-level credit supply variation by weighting the average fitted bank-level credit supply variation[35], [36]. In other words, we first generate fitted firm credit supply variations by using loan-level regression with non-standardized variables, then we standardize fitted

[35]To minimize bias in the fitted credit variation, we add the interest rate compensation in the loan-level regression to control for the omitted variable bias.

[36]The fitted bank-level and firm credit supply variations are based on loan-level regressions with non-standardized variables, but for easier interpretation, we report the coefficient of standardized firm credit supply variations in the firm-level regression.

firm-level variations and use them in firm-level regression.

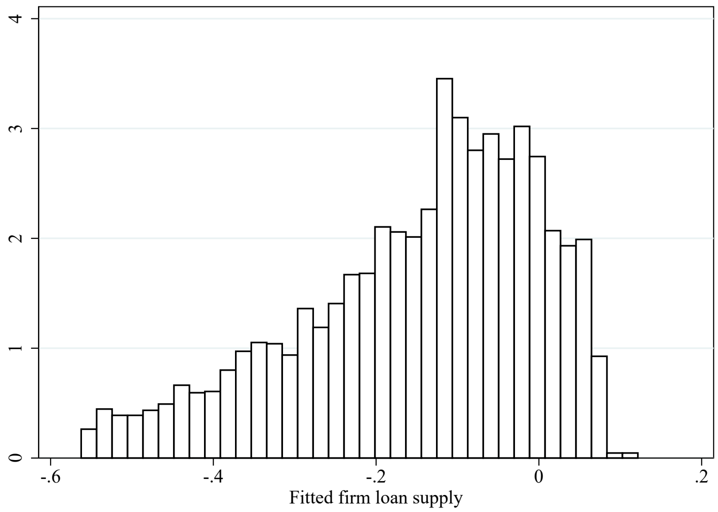


Figure 5: fitted firm-level credit supply effect

This plot shows the fitted firm-level credit supply variation. We constructed the firm-level credit supply variation by weighting the average fitted bank-level credit supply. The fitted bank-level credit supply variations are based on loan-level regressions with non-standardized variables. To control for omitted variables, we included the interest rate compensation as a control variable in the loan-level regression.

Figure 5 presents the firm-level credit supply effect $\Delta supply_j^{AVE}$ for multibank firms. The figure suggests that the majority of firms experienced contractionary credit supply shocks due to the two on-balance sheet mismatches after the Swiss franc appreciation[37].

As discussed in section , we apply equation 3.4 to study the influence of the bank lending channel at the firm level. In order to handle the generated regressor problem, which can bias the standard error of the estimated coefficient in firm-level regression, we use the pairs cluster bootstrap for obtaining standard error. To answer the first question, we used the growth rate of total bank credit for each firm as the dependent variable. The coefficients of the firm-level credit supply effect provide test results for the extent of neutralization. A coefficient of zero would suggest that firms can fully adjust for bank-specific loan increases (decreases) by borrowing less (more) from less affected banks. A positive coefficient suggests that expansionary (contractionary) credit supply loosens (tightens) the borrowing constraint of firms. Table 9 shows the results of the firm-level total bank

[37] The fitted credit supply effect for both multi and single banks is presented in Appendix A.10.

	(1) OLS gm(total loan)	(2) OLS gm(total loan)	(3) OLS gm(total loan)	(4) OLS gm(total loan)
$\Delta supply_j^{AVE}$	0.181***	0.129*	0.153***	0.252***
	(0.076)	(0.055)	(0.006)	(0.027)
$\Delta supply_j^{AVE}$ $\times$ log revenue		0.004		-0.009***
		(0.006)		(0.002)
Bank controls	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes
Fitted FE	Yes	Yes	No	No
R-squared	0.599	0.598	0.524	0.538
Number of observations	4,510	4,459	44,356	43,246
Region $\times$ Industry	Yes	Yes	Yes	Yes

This table examines the firm-level effect of credit supply shock. The outcome variable is the normalized growth rate of firm-level total bank credit, gm(total loan), to firm j between the pre-crisis period (from 2014:Q1 to 2014:Q4) and the post-crisis period (from 2015:Q1 to 2015:Q4). The dependent variable is the firm-level credit supply variation calculated by weighting the average fitted bank-level credit supply variation. The control variables include a set of bank controls, a set of firm controls, fitted firm fixed effects, and region $\times$ industry fixed effects. In column (3), log sales are also included as a control variable. The standard errors are obtained from 1,000 iterations of pairs cluster bootstrapping, this process involves cluster sampling at the firm level, and conducting cluster regression at the regional level. *** denotes significance at the 1% level, ** denotes significance at the 5% level, and * denotes significance at the 10% level.

Table 9: firm level impact: total bank credit

credit regressions. The firm-level credit supply effect yielded a positive and significant coefficient (Column 1), indicating that firms were unable to fully adjust to changes in credit supply by borrowing from banks with low mismatches. A one-standard deviation decrease in firm-level credit supply predicted a 18.1% decrease in the growth rate of firm total credit. This effect was observed not only for multibank firms but also for all firms (Column 3), suggesting that the inability to neutralize credit friction was not limited to multibank firms. Column (2) and (4) revealed heterogeneity in the neutralization of credit friction among firms of different sizes. Previous literature has emphasized that smaller firms may be more vulnerable to negative credit shocks (Bernanke et al. [1994]). We used firm income (log revenue) as a proxy for firm size to test the heterogeneity of the firm-level total credit response. Column (2) and (4) showed that small firms could not fully neutralize the impact of bank lending, estimating a much larger and more statistically significant positive coefficient. These results suggest our finding is consistent with the previous literature, large firms have better ability to offset the impact of credit supply shock.

In light of the result that shocks to the lending channel affect the aggregate borrowing of firms, we further examine the consequences of credit supply variation on corporate behavior. We have two main objectives. The first is to quantify the contribution of bank credit supply shocks to the aggregate change in capital accumulation in the next two years. The second objective is to investigate whether credit supply shocks affected the probability of a firm's liquidation in the subsequent year.

Table 10 provides the results. The table consists of two panels: panel A displays results exclusively for multi-borrowing firms, while panel B shows results for all firms. Columns (1) and (2) reveal results from the cross-sectional regression, identical to equation 3.4, with the dependent variable being the two-year total capital growth rates of firms. When we look at multi-borrowing firms, we find that on average, firms are not significantly influenced by credit supply shocks in terms of capital growth rates(Panel A). However, the impact of credit supply becomes quite significant on firm investment when we analyze full sample that includes firms with multiple borrowing but is primarily made up of those with single borrowing. From column (2) Panel B, we find the coefficient is only positive significant for smaller firms. This suggests that there is heterogeneity in how credit frictions impact the real economy. The potential reason for the insignificant real effect in panel A could be that multi-borrowing firms tend to be larger in size and have better profitability and lower leverage (see Table 2), therefore, they are more likely to have better liquidity conditions to respond to credit supply shocks.

Next, we conduct an analysis to predict a firm's liquidation following the appreciation of the Swiss franc, utilizing the firm-level credit supply effect $\Delta supply_j^{AVE}$. We perform nonlinear probability regressions on the panel including both surviving and exiting firms over the one-year period following the shock. The dependent variable equals one if the firm exited in 2015 and zero otherwise.[38] The results of these probit regressions are given in columns (3) and (4), and they display a pattern similar to the investment analysis. On average, we observe that the firm-level credit supply change ($\Delta supply_j^{AVE}$) impacts the

[38]It's important to note that we don't have data on actual firm liquidation; our information is limited to whether or not a firm has submitted a tax form. In Hungary, a firm might fail to submit tax forms for a few years. This doesn't necessarily indicate liquidation; it could also mean that the firm has temporarily ceased operations.

	(1) OLS g(capital 2y)	(2) OLS g(capital 2y)	(3) Probit Liquidation 1y	(4) Probit Liquidation 1y
Panel A: Multi-borrowing firms				
$\Delta supply_j^{AVE}$	0.023	0.194	-0.031	-0.362
	(0.026)	(0.145)	(0.055)	(0.261)
$\Delta supply_j^{AVE}$ × log revenue		-0.014		0.029
		(0.011)		(0.021)
Fitted FE	Yes	Yes	Yes	Yes
R-squared	0.032	0.039	0.0564	0.0617
Number of observations	4,049	4,021	4,378	4,339
Panel B: Multi and Single-borrowing firms				
$\Delta supply_j^{AVE}$	0.044***	0.225***	-0.041***	-0.115*
	(0.007)	(0.038)	(0.015)	(0.050)
$\Delta supply_j^{AVE}$ × log revenue		-0.017***		0.007
		(0.003)		(0.006)
Fitted FE	No	No	No	No
R-squared	0.060	0.061	0.0271	0.0241
Number of observations	39,455	38,786	43,021	42,146
Bank controls	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes
Region × Industry	Yes	Yes	Yes	Yes

This table examines the real effects of credit supply shocks at the firm level. The outcome variables are the log growth rate of two-year firm-level total capital and a one-year firm liquidation dummy. Panel A shows results for only multi-borrowing firms, and Panel B shows results for all firms. The dependent variable is the firm-level credit supply variation calculated by weighting the average fitted bank-level credit supply variation. The control variables include a set of bank controls, a set of firm controls, fitted firm fixed effects, and region × industry fixed effects. In Columns (2) and (4), log revenue are also included as a control variable. The standard errors are obtained from 1,000 iterations of pairs cluster bootstrapping, this process involves cluster sampling at the firm level, and conducting cluster regression at the regional level.Significance levels are indicated by asterisks: *** denotes significance at the 1% level, ** at the 5%, and * at the 10%.

Table 10: The firm-level total capital growth rate

likelihood of liquidation only in the sample that includes all firms (Panel B), not in the sample exclusively comprising multi-borrowing firms (Panel A). The significant coefficient of $\Delta supply_j^{AVE}$ in column (3), Panel B, reveals a decrease in credit supply leads to an increase in the possibility of liquidation in full sample with all firms. But larger firms in full sample can mitigate this effect (column (4), panel B). This further emphasizes our interpretation that financial friction primarily impacts the operations of smaller firms.

Our findings indicate that changes in credit due to exchange rate shocks primarily affect small firms. This is particularly relevant for Hungary's economy, given its abundance of small businesses. These credit supply changes can result in significant fluctuations in the output of these firms. Given their large presence in the whole country, this volatility can have a broader impact, potentially contributing to larger economic swings in Hungary.

6 Conclusion

Using firm-bank matched data, our study emphasizes the pivotal role of exchange rate shocks on bank credit supply. Prior research has extensively focused on the debt obligations of foreign currency borrowers. However, our analysis expands this view, showing that these shocks don't just affect foreign currency borrowers; they also influence local currency borrowers via the bank lending channel.

Our findings further delve into the role of currency mismatches in determining bank lending post-shock. We confirm that bank-level currency mismatches, measured by the net foreign asset position, significantly impact bank lending. This aligns with existing literature that has given it considerable attention. More notably, we introduce an often overlooked aspect: the bank lending channel influenced by borrower-level currency mismatches. Such mismatches can amplify credit losses during exchange rate shocks. These losses subsequently resonate within the banks' balance sheets, further affecting their lending behaviors.

From a policy standpoint, our results are illuminating. We underscore the importance of banks in transmitting exchange rate shocks to the wider economy. This highlights the necessity for macro-prudential measures to reduce bank exposures to exchange rate risks, especially those indirect exposures from lending to unhedged borrowers. Implementing these policies could mitigate the impact of exchange rate shocks on the real economy. Lastly, our research stresses the significance of including local currency borrowers when evaluating the overall foreign exchange risk in an economy.

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A Appendix tables and figures

A.1 CHF corporate loans by issuing year

Year	number
2001	1
2002	6
2003	4
2004	99
2005	262
2006	584
2007	1665
2008	1570
2009	75
2010	51
2011	48
2012	51
2013	24
2014	22
N	4462

Of the Swiss franc (CHF) corporate loans present on the balance sheets of the 44 sample banks in 2014, 95 percent were issued before 2009. The Credit Registry lists 4,462 CHF corporate loans linked to 3,704 firms in 2014. On average, these loans have a maturity of 8.5 years, which is longer compared to the average maturities of 4.5 years for Euro corporate loans, and 3.7 years for Hungarian forint loans. Post-2008, banks granted CHF loans to only a few hundred firms, likely those with CHF revenues or involved in carry trading.

Table 11: CHF corporate loans in 2014 by issuing year

A.2 Summary statistics for mismatch measurements

	Obs	Mean	Sd	Pc10	Pc90
de facto Direct CHF mismatch	44	-0.0184	0.0312	-0.0418	0.0003
de jure Direct CHF mismatch	44	0.0373	0.0660	0.0000	0.1145
Indirect CHF mismatch	44	0.0094	0.0131	0.0000	0.0336
Systemic CHF mismatch	44	-0.0278	0.0344	-0.0624	0.0000

This table presents summary statistics for the Swiss franc mismatch measurements used in the empirical analysis.

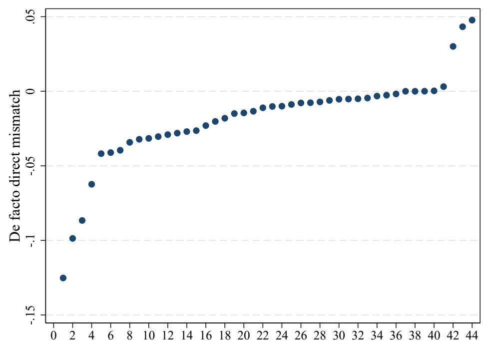
Table 12: Summary statistic mismatch

	Correlation			
	de facto Direct	*de jure* Direct	Indirect	Systemic
de facto Direct	1.00			
de jure Direct	0.06	1.00		
Indirect	-0.05	0.61***	1.00	
Systemic	0.92***	-0.17	-0.42**	1.00

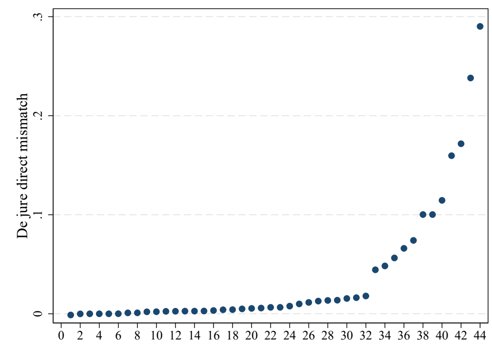
All mismatches are measured in 2014Q4 and expressed as ratio to the bank total asset value.

Table 13: Correlation among mismatch measurements

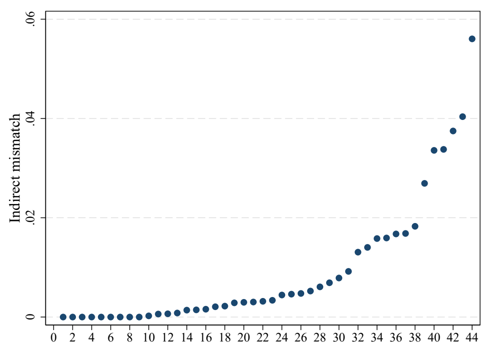
A.3 Distribution plots for mismatch measurements



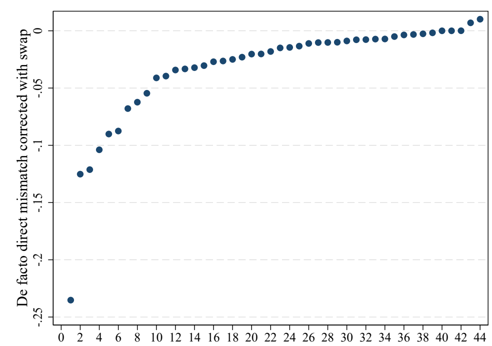
(a) *de facto* Direct mismatch



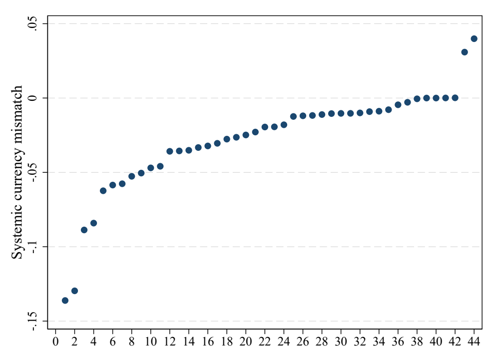
(b) *de jure* Direct mismatch



(c) Indirect mismatch



(d) *de facto* plus off-balance sheet Direct mismatch



(e) Systemic mismatch

Figure 6: Distribution of mismatch measurements

This table presents distribution for the Swiss franc mismatch measurements among 44 banks used in the empirical analysis.

A.4 CHF loan default rate

	CHF	EUR	HUF
Panel A: average late payment days			
2014	521.4	88.2	80.8
	(4,462)	(13,456)	(156,939)
2015	707.8	103.4	95.9
	(3,709)	(12,877)	(156,167)
net increase rate	35.75%	17.23%	18.69%
	CHF	EUR	HUF
Panel B: share of defaulted loans			
2014	38.55	8.26	7.70
	(4,462)	(13,456)	(156,939)
2015	42.36	7.87	7.50
	(3,709)	(12,877)	(156,167)
net increase rate	9.88%	-6.87%	-2.67%

Table 14: Statistics for the CHF loan default rate

Panel A of the graph provides a comparative overview of the average number of late payment days across different currencies. On the other hand, Panel B offers insight into the proportion of defaulted loans per currency. A loan is categorized as defaulted if a payment is delayed by more than 90 days, a standard classification in financial literature.

An interesting trend emerges from the data: both the average number of late payment days and the share of defaulted loans for Swiss franc loans saw a significant increase between the years 2014 and 2015. This rise is particularly notable when compared to loans denominated in Euros or Hungarian forints, which did not exhibit the same level of increase. These findings suggest a potential link between the currency type and borrower repayment patterns. Given the unexpected appreciation of the Swiss franc during this time, it's plausible that this played a significant role in influencing repayment behaviors, particularly for Swiss franc loans. This currency's sharp rise in value could be a key contributor to the observed increase in late payments and loan defaults.

A.5 Summary statistics for bank variables

	Obs	Mean	Sd	Pc10	Pc90
ROA	44	-0.45	1.47	-2.20	0.59
Non performing loan ratio	44	0.11	0.07	0.04	0.19
Log Total Asset	44	11.33	1.96	9.29	14.49
Tier 1 capital ratio	44	0.17	0.06	0.12	0.26
Log RWA	44	10.53	2.12	8.40	13.98
Loan to deposit ratio	44	1.02	1.46	0.37	1.67
CAR	44	18.30	5.56	13.27	28.04
Loan to RWA	44	0.95	0.27	0.64	1.22
CHF loan to RWA ratio	44	0.13	0.13	0.02	0.30
Foreign funding to RWA ratio	44	0.20	0.40	0.03	0.10
Loan from parent bank to RWA ratio	44	0.13	0.20	0	0.40

This table presents summary statistics for the bank-level variables used in the empirical analysis.

Table 15: Summary statistic bank

A.6 the Bank lending channel and net CHF swap position

	(1) FE gm(loan)	(2) FE gm(loan)
DMismatch^{f}	0.189***	
	(0.042)	
DMismatch^{swap}		0.064***
		(0.017)
IDMismatch	-0.084***	-0.081***
	(0.021)	(0.029)
Net Swap position	0.083***	
	(0.022)	
Bank Controls	Yes	Yes
R^2	0.398	0.396
Number of observations	10,052	10,052
Firm fixed effect	Yes	No
Bank type	Bank	Bank
Firm borrowing type	Multiple	Multiple

This table examines the role of banks' net Swiss franc swap position in transmitting the exchange shock to credit supply. The outcome variable is the normalized growth rate in loans (gm(loan)) granted by bank b to firm j between the pre-crisis period (from 2014:Q1 to 2014:Q4) and the post-crisis period (from 2015:Q1 to 2015:Q4). All columns include a set of bank controls, which are (1) loan to risk-weighted assets ratio, (2) loan to deposit ratio, (3) low tier one capital dummy, (4) capital adequacy ratio, (5) loan loss provision to risk-weighted assets ratio, (6) total deposits to liability ratio, (7) return on assets, (8) liquidity to risk-weighted assets ratio, and (9) inter-bank deposits in liabilities to risk-weighted assets ratio. The models are estimated on the sample of firms with multiple lending relationships and include firm fixed effects. The model in Column 1 includes the net Swiss franc swap position measured in 2014Q4, while in Column 2, the direct Swiss franc mismatch is adjusted by the net swap position (total on and off-balance sheet net asset position). Standard errors are clustered at the bank level. *** denotes significance at the 1% level, ** at the 5%, and * at the 10%.

Table 16: The bank lending channel:swap

We also implement a experiment to test the the impact of sum of on and off-balance sheet mismatches on post-shock credit supply, we construct the total on and off-balance sheet direct mismatch using the measurement:

$$\text{DMismatch}_i^{\text{swap}} = \text{DMismatch}_i^{f} + \frac{\text{net CHF swap}_i}{\text{Total bank assets}_i}$$

We then conduct a difference-in-differences regression analysis using $\text{DMismatch}_i^{\text{swap}}$

and IDMismatch$_i$ and report the results in column (2). The findings suggest that a one-standard-deviation increase in the sum of on and off-balance sheet asset positions predicts an approximately 6.4% increment in credit supply after controlling for firm-specific demand.

A.7 Parallel trends assumption for the systemic mismatch exposure

	(1)
	FE
	gm(loan)
SMismatch	-0.205***
	(0.037)
Bank Controls	Yes
R^2	0.398
Number of observations	10,052
Firm fixed effect	Yes
Bank type	Bank
Firm borrowing type	Multiple

The table presents regression result using the systemic mismatch measure as the independent variable. The outcome variable is the normalized growth rate in loans ($gm(loan)$) granted by bank b to firm j between the pre-crisis period (from 2014:Q1 to 2014:Q4) and the post-crisis period (from 2015:Q2 to 2015:Q4). The regression includes a set of bank controls that are the same as those used in the baseline regression. Standard errors are clustered at the bank level. The notation *** indicates statistical significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.

Table 17: The bank lending channel:Robustness test with alternative measurement

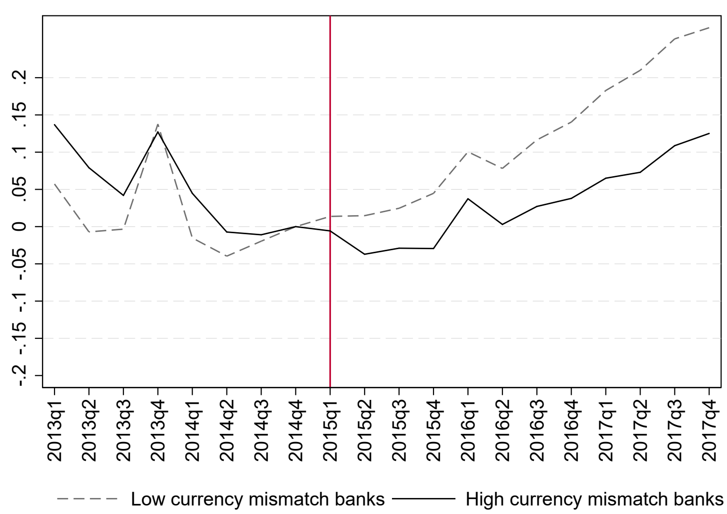


Figure 7: The bank lending channel at aggregate level

This plot tests the assumption of parallel trends at the aggregate level for systemic mismatch exposure. We divided the banks in the final sample into two groups: "High systemic mismatch" and "Low systemic mismatch," based on their systemic mismatch exposure in 2014 Q4. Then, we plotted the aggregate loan stock volume in forints of the two groups, normalizing each on the y-axis to 0 in 2014 Q4. The plot in 7 confirms that the significant divergence in loan stock volume trends after the Swiss franc appreciation cannot be attributed to pre-existing differences.

A.8 Further test for robustness of measurements

	(1)	(2)	(3)
	FE	FE	FE
	gm(loan)	gm(loan)	gm(loan)
DMismatch^f	0.192***	0.183***	0.207***
	(0.040)	(0.037)	(0.029)
IDMismatch	-0.097***	-0.101***	-0.096***
	(0.022)	(0.021)	(0.021)
Bank Controls	Yes	Yes	Yes
R^2	0.398	0.399	0.399
Number of observations	10.052	10.052	10,052
Firm fixed effect	Yes	Yes	Yes
Firm borrowing type	Multiple	Multiple	Multiple

This table presents robustness tests using alternative methods of measurement construction. The dependent variable is the normalized growth rate in loans, denoted as gm(loan), which is given by bank b to firm j between the pre-crisis period (2014:Q1 to 2014:Q4) and the post-crisis period (2015:Q1 to 2015:Q4). The primary independent variables are the bank's direct and indirect exposures to Swiss franc mismatches, as measured in 2014:Q4. In column (1), we additionally include the Swiss franc market security into the direct mismatch measurement for Swiss franc assets. In column (2), we omit the Swiss franc lending to foreign-owned firms from the indirect mismatch. In column (3), we exclude the Swiss franc provision from the liabilities. All columns incorporate a suite of bank controls, including: (1) loan to RWA ratio, (2) loan to deposit ratio, (3) low Tier 1 capital dummy, (4) capital adequacy ratio, (5) loan loss provision to RWA ratio, (6) total deposits to liability ratio, (7) return on assets, (8) liquidity to RWA ratio, (9) inter-bank deposits in liabilities to RWA ratio, and (10) CHF swap to RWA ratio. All models, estimated on a sample of firms with multiple lending relationships, include firm fixed effects. Standard errors are clustered at the bank level. Significance levels are marked as *** for 1

Table 18: The bank lending channel:alternative measurements

A.9 Results for the alternative specification

	(1) g(loan)	(2) g(loan)	(3) g(loan)	(4) g(loan)
Post	0.455***	0.517***	0.221***	0.264***
	(0.017)	(0.024)	(0.005)	(0.007)
DMismatch^f*Post	0.788**	0.654***	1.459***	1.466***
	(0.214)	(0.216)	(0.059)	(0.059)
IDMismatch*Post	-2.195***	-2.130***	-0.829***	-0.937***
	(0.534)	(0.538)	(0.155)	(0.157)
Bank Controls	Yes	Yes	Yes	Yes
Firm Control	No	Yes	No	Yes
R^2	0.682	0.681	0.884	0.881
Number of observations	59,302	58,711	325,009	319,488
Firm Fixed effect	Yes	Yes	Yes	Yes
Industry Fixed effect	No	Yes	No	Yes
Region Fixed effect	No	Yes	No	Yes
Time Fixed effect	No	Yes	No	Yes
Firm borrowing type	Multiple	Multiple	Multiple&Single	Multiple&Single

This table presents various robustness tests for alternative specifications aimed at capturing quarterly variations. The dependent variable is the logarithm of the loan volume between bank b and firm j at quarter t. The primary independent variables are the bank's direct and indirect exposures to Swiss franc mismatches, both multiplied by the post-shock dummy. These exposures are not standardized. Every column incorporates bank controls, including: (1) loan to RWA ratio, (2) loan to deposit ratio, (3) low tier one capital dummy, (4) capital adequacy ratio, (5) loan loss provision to RWA ratio, (6) total deposits to liability ratio, (7) return on assets, (8) liquidity to RWA ratio, (9) inter-bank deposits in liabilities to RWA ratio, and (10) CHF swap to RWA ratio. Columns 1 and 2 focus on multiple-relationship firms, while Columns 3 and 4 cover both single- and multiple-relationship firms. Columns 2 and 4 further incorporate additional industry, region, and time fixed effects. Standard errors, clustered at the bank level, are denoted as follows: *** for significance at the 1% level, ** for the 5%, and * for the 10%.

Table 19: The bank lending channel:quarterly difference in difference

A.10 Fitted firm-level credit supply for multi and single bank firms

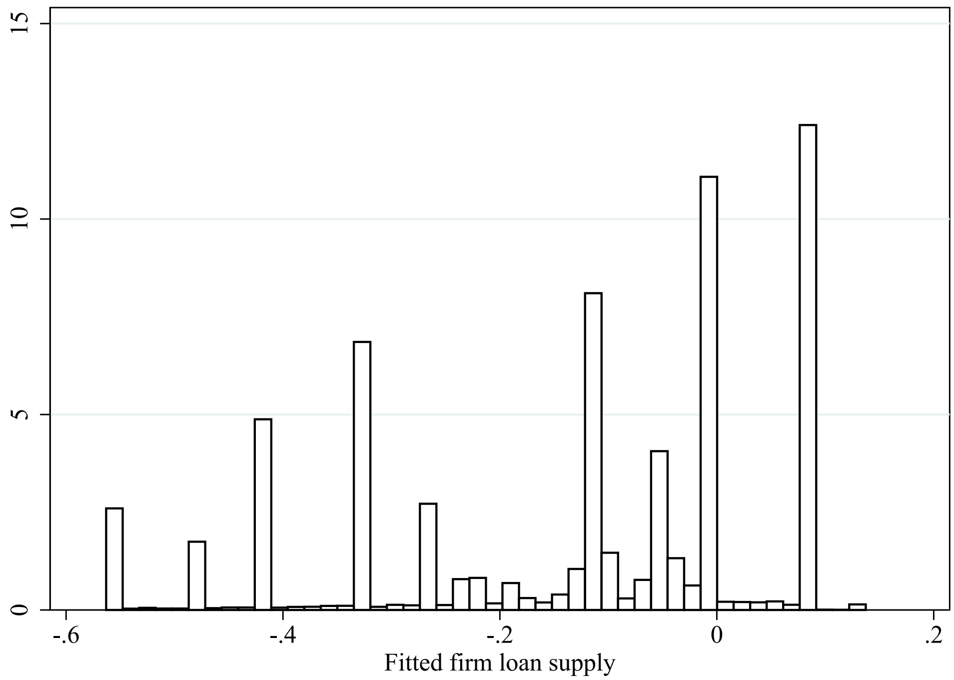


Figure 8: Fitted firm-level credit supply for multi and single bank firms

This plot displays the fitted credit supply at the firm-level for both multi-bank and single-bank firms. The spikes in the plot are a result of many single-bank firms having 100% loan share from only one bank, meaning that the spikes represent the exact loan supply of a bank.