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

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Abstract

In this paper, we explore the effects of two types of currency mismatches on banks' balance sheets - net foreign currency asset positions and lending to unhedged borrowers - in the transmission of exchange rate shocks to local currency borrowers. Utilizing the unexpected appreciation of the Swiss franc in January 2015 as a case study, and making use of Hungarian credit registry data, our results establish a positive correlation between banks' net Swiss franc asset positions prior to the shock and loan growth following the shock. Conversely, lending to unhedged firms prior to the shock negatively impacts loan growth in its aftermath. The credit supply response to exchange rate shocks is heterogeneous and is contingent upon the exposure structure of individual banks' balance sheets to net Swiss franc assets and lending to unhedged borrowers. This response can either result in contraction or expansion. Moreover, we provide evidence suggesting that fluctuations in bank credit supply considerably affect small firms' investment activity and their probability of default after a shock.

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

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

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1 Introduction

Exchange rate shocks can frequently cause financial distress for those borrowing in foreign currency in emerging markets. Models of open economy macroeconomics suggest that large mismatches between foreign currency assets and unhedged liabilities on borrowers' balance sheets can create a link between these shocks and the real economy. This link, known as the "balance sheet effect", comes into play when a depreciation in the domestic currency increases the net domestic currency value of liabilities in foreign currency. As a result, it weakens balance sheet positions and limits firms' ability to invest and grow (Krugman [1999], Céspedes et al. [2004]).

Existing empirical studies have largely been concerned with the financial distress of foreign currency borrowers in currency crises. However, it's also been observed that local currency borrowers, who aren't directly exposed to exchange rate risks, experience substantial impacts after exchange rate shocks (Verner and Gyöngyösi [2020]). The role of financial intermediaries is crucial here, as they help transmit these shocks to local currency borrowers and the broader real economy. Importantly, these shocks can trigger shifts in the capital and liquidity on banks' balance sheets, indirectly influencing firms via what is often referred to in economic literature as the "bank lending channel."

This paper explores the behavior in which the bank lending channel conveys exchange rate shocks to local currency borrowers and the real economy, employing micro-level data. In emerging economies, the impacts of an exchange rate shock on a bank primarily arise from two types of currency mismatches on the balance sheets. The first type is the difference between foreign currency assets and liabilities, known as the bank's net foreign currency asset position. Similar to the borrower-level "balance sheet effect," a bank's net foreign currency asset position is reevaluated following an exchange rate shock, subsequently affecting the net worth and liquidity. The second type involves an indirect currency mismatch, characterized by foreign currency loans to unhedged borrowers. While these loans are classified as foreign currency assets on the bank's balance sheet, they carry significant mismatch risk for borrowers, increasing credit risks for banks. A substantial depreciation in the exchange rate can transform a large portion of loans to households and non-financial firms into non-performing loans due to the borrower-level "balance sheet effect." Consequently, the indirect currency mismatch can weaken the bank's income flow if the borrower is unable to repay the loan following depreciation (Ranciere et al. [2010]).

Many empirical studies have looked into the effect of foreign currency risk exposure on firms' (Kim et al. [2015], Kalemli-Ozcan et al. [2016]) and banks' balance sheets (Agarwal [2018], Abbassi and Bräuning [2021]). However, micro-level evidence on how currency exposure on balance sheets impacts bank credit supply after an exchange rate shock, especially in emerging economies, is still limited. This study aims to address this issue by exploring the bank lending channel of exchange rate shocks in Hungary, focusing specifically on an episode of Swiss franc appreciation in January 2015. This appreciation event serves as an ideal case study for investigating how exogenous exchange rate shocks spread to the real economy through bank lending in Hungary for two reasons. First, the appreciation was an unexpected, external shock for Hungary. Second, like other Central and Eastern European (CEE) countries, Hungary had a high level of "Swiss francization" before 2015, with a notable presence of Swiss franc assets on banks' balance sheets and a dependence on wholesale funding to refinance Swiss franc loans. Therefore, the Swiss franc appreciation likely significantly affected the balance sheets of Hungarian banks.

2 Main Results

In this paper, we introduce two bank-level indicators to quantify banks' exposure to the two types of Swiss franc mismatches, capable of transmitting the exchange rate shock as previously discussed. Both indicators were recorded prior to the Swiss franc appreciation shock. The first indicator is the banks' net Swiss franc asset position, referred to here as the direct mismatch measurement.[1] The second indicator is the lending to unhedged firms, named as the indirect mismatch measurement in our study. To investigate the bank lending channel of the exchange rate shock, we apply within-firm difference-in-difference regressions using loan-level data from the Hungarian credit registry as our primary research design. This approach allows us to separate the effect of shifts in credit supply from simultaneous changes in firms' credit demand and creditworthiness (Khwaja and Mian [2008]). To mitigate potential bias arising from off balance sheet currency mismatch, we adjust for the possible impact of value changes in swap contracts following the Swiss franc appreciation. This adjustment is carried out by incorporating the net Swiss franc swap ratio as a control variable in all our analyses.

Our loan-level analysis led to the following key findings. We compared the lending to the same firm by two banks with a one standard deviation difference in their net Swiss franc asset positions. Our comparison showed that the bank with the larger net asset position increased its credit supply by 19% more than the bank with the smaller position. This result suggests that a bank's net Swiss franc asset position directly impacts its ability to provide credit after the exchange rate shock. Banks with larger net asset position is better off after shocks. Further, our findings show that banks with more Swiss franc loans to unhedged firms experience lower loan growth after the shock compared to banks with fewer such loans. Specifically, a one standard deviation increase in loans to unhedged firms led to a decrease in loan growth by about ten percentage points after the shock. This under-

[1] We adjust the net Swiss franc asset position by the total household Swiss franc lending, as all household Swiss franc loans were converted to Hungarian forints following a bill passed in November 2014, yet remained recorded as Swiss franc loans on banks' balance sheets.

lines the idea that banks with more exposure to unhedged firms get the negative effects of exchange rate shocks more strongly. In robustness tests, We control for the influence of concurrent policy effects and external market funding to ensure the reliability of our results. In addition, we discovered that the effects of two types of Swiss franc mismatches affected both the extensive and intensive margins of credit supply. Given the heterogeneity in the net Swiss franc asset positions and the volumes of lending to unhedged firms across Hungarian banks, our findings point to varying responses of bank credit supply to exchange rate shocks. For banks with significantly positive net Swiss franc assets and low levels of lending to unhedged firms, the response appears to be expansionary. Conversely, for banks with negative net Swiss franc asset positions or high levels of lending to unhedged firms, the reaction is contractionary.

We then explore how exchange rate shock transmits to bank lending activities. We find that the revaluation of the net Swiss franc asset position is particularly prominent for banks with low liquidity. However, we find no evidence that the effect is stronger for banks with low capital ratios. These findings suggest that the revaluation effect mainly works through the unexpected change in banks' cash flow, which can vary the banks' liquidity condition. On the other hand, we observed that banks with higher liquidity and capital ratios could offset the credit supply effect induced by the firm loan credit loss. This suggests that the indirect mismatch impacts the credit supply because the realized credit loss impairs both liquidity condition and capital buffer.

Building on our loan-level analysis, we now shift our focus to examine how corporate operations are affected by exchange rate shocks via the bank lending channel. Our first step is to use the estimated coefficients from our loan-level findings. From these results, we calculate how much the supply of credit for each individual banks changed due to their pre-shock position in Swiss franc assets (direct mismatch) and their lending to unhedged firms(indirect mismatch). We then construct a measure for firm-level credit supply change by averaging the calculated changes in credit supply for each bank, giving more weight to banks that lent larger amounts. This measure helps us quantify how large is the credit supply changed by exchange rate shock in individual firm level. To address the potential bias in the standard error in the firm-level regression, due to the generated regressor, we apply a bootstrapping method to obtain standard error. Our firm-level regression shows that a one standard deviation decrease in firm-level credit supply variation before the Swiss franc shock leads to an 18% decrease in the total bank borrowing growth for firms borrowing from multiple banks. This suggests that these firms cannot fully counteract credit supply variations simply by adjusting their borrowing from other banks. Importantly, this effect is significant only for smaller firms, indicating that larger firms are better equipped to manage variations in credit supply. Next, we examine how bank lending channels affect firms' real activities. We find that for firms borrowing from multiple banks, the bank lending channel does not significantly influence operational activities, even though it has a significant effect on total credit. This may be because these firms are generally larger and more profitable, allowing them to maintain their production using internal liquidity. In contrast, for smaller firms in the sample with both multi-borrowing and single-borrowing firms, changes in credit supply positively affect their investment activities but negatively impact their likelihood of liquidation. For larger firms, we find no significant effect of credit supply variations on their real activities.

3 Related literature

This paper contribute to the existing literature on the transmission of exchange rate shocks via the bank lending channel, specifically within the context of emerging markets. Previous studies have largely examined this phenomenon in advanced economies. 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. In contrast to previous research such as Agarwal [2018] and Abbassi and Bräuning [2021][2], which discusses the impact of exchange rate shocks on bank lending behavior in advanced economies, we recognize two distinct transmission channels relevant to emerging markets: net foreign asset positions and lending to unhedged foreign borrowers. The latter is especially significant as it presents a channel for systemic risk exposure, a concept supported by prior literature (Ranciere et al. [2010]). Additionally, our study expands the literature on spillover channels, encompassing exposed and unexposed lenders. For instance, Gupta [2019] have provided evidence of foreclosure spillovers through peer effects, while Huber [2018] have demonstrated that bank lending contractions can affect other local firms via negative demand spillovers. In our work, we establish that lending to unhedged foreign borrowers is correlated with a post-exchange rate shock decrease in credit supply. This observation implies that the credit risk of exposed borrowers can influence the bank balance sheet, which further spills over to other borrowers by reducing the credit supply.

Our analysis intersects with two main strands of literature: The first is the transmission of banking activities to the real economy. This research builds upon the seminal works of Bernanke and Gertler (Bernanke [1983], Bernanke and Blinder [1988]), and includes numerous empirical studies showing that negative shocks to banks can lead to lending contractions that impact the real economy.[3] To this strand of literature, our study contributes by demonstrating the crucial role of the bank lending channel in transmitting exchange

[2] Agarwal [2018] aligns with our concept of the direct mismatch, namely the net foreign currency asset position. Abbassi and Bräuning [2021] consider the mismatch as banks' on- and off-balance sheet net foreign currency positions, focusing specifically on the off-balance sheet contract between banks and firms.

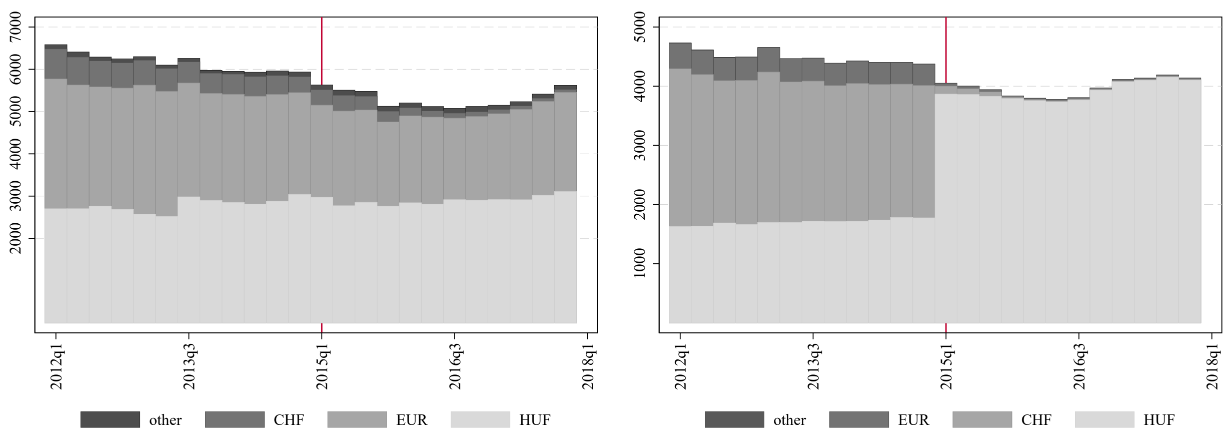
[3] For instance, studies like Khwaja and Mian [2008], Schnabl [2012], Cingano et al. [2016] have shown that firms borrowing from banks that experience declines in liquidity witness lower loan growth and investment. Similarly, research exploiting the European sovereign debt crisis (Popov and Van Horen [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]).

rate shocks and establishing that the bank lending response can be contractionary or expansionary. The second area relates to foreign currency debt in international finance.[4] Here, 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 4 offers institutional background and details the measurement of currency mismatch exposures. Section 5 discusses the empirical framework and presents summary statistics of the data. Sections 6 and 7 report the results of the bank lending channel analysis at the loan and firm levels, respectively. Finally, Section 8 concludes.

4 Institutional background and Currency mismatch exposures measurements

4.1 Institutional background



(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.

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

[4]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.

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. Particularly in Hungary, the foreign currency debt held by households and non-financial corporations accounted for nearly 50% of the total outstanding debt. According to official statistics, a considerable part of this debt was in Swiss francs[5] (see Figure 1).

This exposure to Swiss franc risk was due to several factors, including the stability of the Swiss franc and lower interest rates compared to local currencies, 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), catching these economies off-guard.

Figure 2: Exchange rate around the shock

This figures show the daily nominal CHF/HUF exchange rates from 2012 to 2017.

The sudden and unanticipated exchange rate shock had a pronounced impact on the val-

[5]In the fourth quarter of 2014, the share of Swiss franc assets to total assets stood at 13%, and the share of Swiss franc liabilities to total assets had declined to 6% in the Hungarian banking sector.

uation of debt held by hundreds of thousands of households and firms in the CEE countries, leading to an increase in non-performing loans and augmented credit risk on bank balance sheets. This, in turn, led to disruptions in the functioning of the banking system. This exposure to Swiss franc risk manifested in two specific mismatches in these economies: a direct mismatch, given by the net foreign asset position, and an indirect mismatch due to lending to unhedged borrowers.

In Hungary, measures to mitigate foreign exchange risk were implemented before the currency shock occurred. On November 25, 2014, the Hungarian Parliament passed a bill authorizing the Central Bank of Hungary to convert foreign currency household mortgage loans into Forint loans using foreign reserves. Though originally intended as a measure to manage household foreign exchange risk, this step fortuitously protected the household sector from the subsequent currency shock. The exchange rate for this conversion, determined on November 7, 2014, effectively transformed household foreign currency mortgage debt into Forint contracts, insulating households from the appreciation of the Swiss franc.

However, this measure did not eradicate the systemic exposure of the Hungarian banking system to Swiss franc volatility. It only mitigated the direct exposure of households, leaving banks with significant levels of Swiss franc-denominated debt. Furthermore, it did not address the indirect exposure due to lending to unhedged firms; a considerable portion of corporate debt was still vulnerable to Swiss franc fluctuation. Consequently, the banking system remained a conduit for transmitting the Swiss franc shock to the broader economy via changes in credit supply, based on the structure of the banks' balance sheets, despite the removal of foreign currency household debt. As a result, even though the household sector was shielded, the risk persisted for banks and unhedged corporate borrowers, extending the influence of the Swiss franc shock on the Hungarian economy.

4.2 Hypotheses Development and Measurement of Currency Mismatch Exposure

In this section, we describe how the Swiss franc appreciation shock affected the Hungarian economy through changes in credit supply. We focus on two main pathways related to banks' balance sheets.

The first pathway involves the Swiss franc mismatch on bank balance sheets, also known as the net Swiss franc asset position. If a bank holds more Swiss franc assets than liabilities, a sudden appreciation of the Swiss franc exchange rate can instantly increase the bank's net worth and reduce the debt burden. On the contrary, if a bank's Swiss franc liabilities exceed its assets, the same appreciation can reduce its net worth and increase debt burden. These change has important implications for a bank's lending capacity. First, the revaluation can directly change the liquidity constraint faced for banks, especially if their Swiss franc asset and liability are in short term 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.

A secondary path through which the Swiss franc appreciation shock influences credit supply involves the considerable volume of Swiss franc-denominated corporate loans. These loans persisted on bank balance sheets despite the phase-out of households' foreign currency debt[6]. 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 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.

[6]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.

As we outlined above, in this paper, we focus on two types of Swiss franc mismatches, both of which contribute to how exchange rate shocks lead to changes in 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 this discussion, 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 Swiss franc asset position before the appreciation shock, were more likely to increase their credit supply in the period following the shock.
- **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 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:

$$\text{DMismatch}_i^j = \frac{\text{CHF assets}_i - \text{CHF liabilities}_i}{\text{Total bank assets}_i} \tag{4.1}$$

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, due to regulatory requirements and the high demand for Swiss franc loans.

***de facto* Direct Mismatch**

The calculation of the *de jure* direct mismatch may not reflect the actual net Swiss franc asset position of each bank. This is due to the compulsory conversion program, introduced in February 2015, that required foreign currency-denominated household loans to be converted to forint-denominated household loans. However, this conversion was effectively completed much earlier, with the exchange rate for conversion fixed at the market rate on November 7th, 2014. As a consequence, Swiss franc loans to households were no longer considered as Swiss franc assets. Hence, when determining the pre-shock exposure measurement, we need to subtract Swiss franc loans to households from Swiss franc assets, even though these loans were still recorded as Swiss franc assets on bank balance sheets before the shock. Formally, we express the *de facto* direct mismatch measurement for bank i as:

$$\text{DMismatch}_i^f = \frac{\text{CHF assets}_i - \text{CHF liabilities}_i - \text{CHF lending to households}_i}{\text{Total bank assets}_i} \tag{4.2}$$

Indirect Mismatch

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

$$\text{IDMismatch}_i = \frac{\text{CHF lending to unhedged firms}_i}{\text{Total bank assets}_i} \tag{4.3}$$

$IDMismatch_i$ 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 conversion program and the pre-determined exchange rate. These factors 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. This is evidenced by a considerable increase in the average number of late payment days for CHF loans in 2015 compared to 2014 and relative to HUF and EUR loans.

5 Empirical framework and data description

5.1 Empirical framework

5.1.1 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:

$$gm(loans_{b,j}) = \beta_0 + \beta_1 DMismatch + \beta_2 IDMismatch + \Gamma X + \rho_j + \epsilon_{b,j} \tag{5.1}$$

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.

Moreover, our analysis allows us to add the firm fixed effect only for firms involved in multiple borrowing relationships. In the absence of fixed effects, a standard ordinary least squares (OLS) estimator could yield biased estimates for the lending coefficient β_1 if the contractions in credit supply, attributable to bank currency mismatches, correlate with unobserved changes in firm-specific credit demand (Bottero et al. [2020]). Depending on the specific regional economic context, such as whether firms are located in regions dominated by companies with Swiss franc liabilities or in areas dominated by exporters to Switzerland, this correlation could manifest either positively or negatively. For instance, following the appreciation of the Swiss franc, firms in the former region might face regional economic downturns and decrease their credit demand, whereas firms in the latter region might experience a positive impact and potentially increase their loan uptake. Using an OLS estimator for the coefficient of the direct mismatch[7], 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, 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 [8]. This is further supported by the forward exchange rate on January 14th [9] which indicated that the market did not anticipate the event, and Switzerland's prior steadfast commitment to the euro [10]. Therefore, we consider this event to be exogenous and unforeseen for the Hungarian economy, allowing us to discount any pre-emptive adjustments by banks and firms.

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

[8] 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

[9] 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.

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

5.1.2 Firm-level corporate behaviour

After examining the impact of bank Swiss franc mismatches and the unexpected exchange rate shock on bank lending, 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 may 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 level using the results from our loan-level analysis[11]:

$$\Delta supply_b = \hat{\beta}_1 DMismatch_b + \hat{\beta}_2 IDMismatch_b \tag{5.2}$$

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:

$$\Delta supply_j^{AVE} = \sum_{b \in \mathbf{B}j} wbj \times \Delta supply_b \tag{5.3}$$

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.

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

[11] 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.

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 characterizing 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:

$$y_j = \alpha_0 + \alpha_1 \Delta supply_j^{AVE} + \Gamma X_j^{AVE} + \Pi V_j + \rho^{industry} \times \rho^{region} + \hat{\rho}_j + \mu_j \tag{5.4}$$

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[12], 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 unknown parameters, namely coefficients, to create a predicted value. To correct this bias, we use the pairs cluster bootstrap method. For each bootstrap cycle, we select a sample of firms and their associated loans. We 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.

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

5.2 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 5.1, we restrict our main sample to firms that obtained loans from at least two banks and only had Hungarian forint denominated loans as of the end of 2014.

For the same quarter, 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.

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.

	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 as of the end of 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

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 4,5143 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 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 dataset includes 121 financial intermediaries, but many of them are small regional saving institutions that lack complete balance sheet information. Therefore, we limit our sample to the 23 commercial banks operated in national level and 21 big local saving institutions with at least 1% CHF asset in 2014. 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.

	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.

Table 2: Summary statistic firm

6 The bank lending channel

6.1 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 bank credit supply to firms following the Swiss franc appreciation. Column (1) reports the results using the KM framework (FE estimation) specified in Equation 5.1, 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

	(1) FE gm(loan)	(2) OLS gm(loan)	(3) OLS gm(loan)	(4) FE 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

franc assets, after controlling for firm-specific demand[13]. 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%[14] more than the lender with a lower position.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

[13]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

[14]All mismatch measurements are standardized.

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 coefficients 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:Q4, including both single- and multiple-borrowing. The two mismatch risk exposure coefficients are statistically significant at the 1% level. Considering the previous discussion where OLS estimation results were underestimated, 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 a less significant 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. Overall, our results sheds 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 fig-

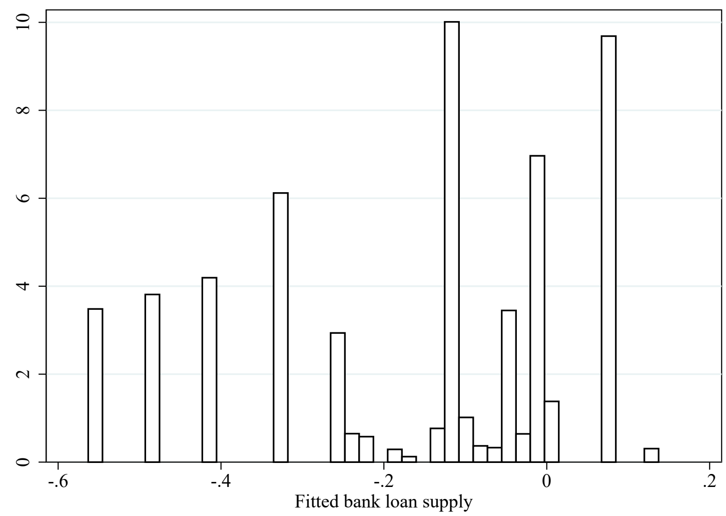


Figure 3: fitted bank-level credit supply effect

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.

ure 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. One crucial reason for the contractionary fitted credit supply in the post-shock period is the conversion program. Due to this program, banks' holdings of Swiss franc assets significantly declined because Swiss franc household loans became forint-denominated assets. This reduction resulted in most banks having more Swiss franc liabilities than assets (negative net Swiss franc asset position). Consequently, banks had higher debt burdens and reduced their credit supply after the Swiss franc appreciation.

Our analysis primarily focuses on the impact of two on-balance sheet mismatches on bank lending, with the net Swiss franc swap position serving as a control for potential off-balance sheet mismatch impact. 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 5.1. 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. To further explore the impact of both 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.

6.2 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 headline results.

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 headline 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[15] in each sample and check whether our headline results change. We should expect the coefficients to remain unchanged if our headline results are not driven by market funding because only large firms in an economy can access the bond or equity market[16]. 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.

[15] Firm size is proxied by total assets.

[16] 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.

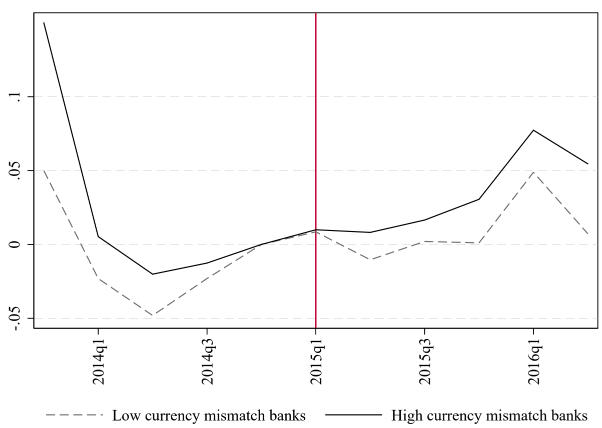
	(1)	(2)	(3)	(4)
	FE	OLS	FE	OLS
	gm(loan)	gm(loan)	gm(loan)	gm(loan)
DMismatch^f	0.197^{***}	0.117^{***}	0.293^{***}	0.132^{***}
	(0.045)	(0.015)	(0.053)	(0.023)
IDMismatch	-0.087^{***}	-0.034^{***}	-0.088^{***}	-0.041^{***}
	(0.026)	(0.008)	(0.021)	(0.008)
Bank Controls	Yes	Yes	Yes	Yes
Interest rate 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%.

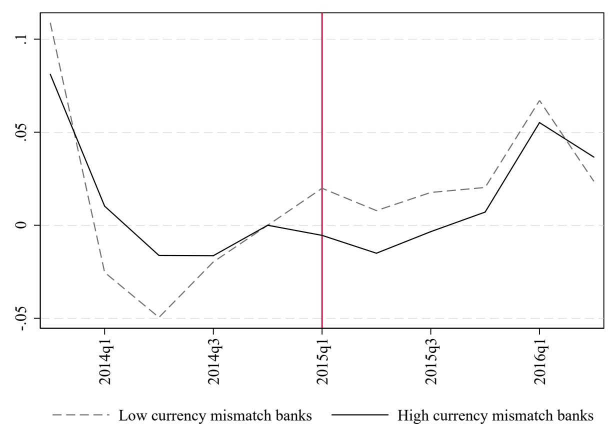
Table 4: The bank lending channel: Robustness tests for alternative explanations

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 "penalty" 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 at the aggregate level. To do so, we follow the method proposed by Bottero et al. (2020) and first sort the 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[17]. 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 the semi-parametric 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. In both sorts, there was no difference in the trend of aggregate credit supply before the shock between banks with high and low Swiss franc mismatch exposure. Therefore, the divergence in trends right

[17]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.

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[18]. 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)	(2)
	FE	OLS
	gm(loan)	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 5.1. 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 penalty 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

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" variable is a dummy that equals

[18] 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.

	(1) FE Exit	(2) OLS Exit	(3) FE g(loan)	(4) OLS 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

one when a 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 the intensive margin effects 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). 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 behind this measurement is similar to our own measures. [19] Specifically, we construct a bank-level "systemic" Swiss franc mismatch exposure as follows:

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

	(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 7: The bank lending channel:Robustness test with alternative measurement

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. This is because, according to our headline results, each component of the systemic

[19] 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.

mismatch measurement should yield a negative effect on credit supply. We report the results in table 7, column (1). The coefficient estimated from the KM framework is positive and significant at the 1% level. This result is consistent with our headline result and expectation. The systemic Swiss franc mismatch exposure is negative for most banks in our sample, suggesting that the collective effect of the two mismatches on bank balance sheets, along with the conversion program before the Swiss franc appreciation, is associated with subsequent significant declines in lending to firms. 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 18.3% after controlling for firm-specific demand. We report the test of the parallel trends assumption at the aggregate level for the systemic mismatch exposure in the appendix.

In Appendix Table A.8, we conduct a robustness check of our main findings using an alternate 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 quarter t. 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[20]. 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.

6.3 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. We first discuss the credit supply variation caused by the direct Swiss franc mismatch exposure. The underlying hypothesis is straightforward and follow we discussed in the hypothesis development : banks with larger net Swiss franc asset

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

positions see a positive revaluation, resulting in an increase in capital and liquidity which shape the bank's lending capacity. Therefore, given the Swiss franc appreciation shock, we anticipate banks with low capital or insufficient liquidity to display higher marginal credit supply growth compared to banks with more capital and/or ample liquidity.

Secondly, we investigate the transmission channels of the contracting credit supply caused by exposure to indirect Swiss franc mismatch. The basic hypothesis here is that 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 this shock, we would expect banks in better capital positions or with more liquidity to be able to offset this contractionary shock.

To examine the transmission channels, we introduce interaction terms between exposure measurements and a set of bank characteristics that serve as proxies for various balance sheet transmission channels, while always including the direct effect. The interaction terms are dummy variables that take a value of one if the observation is higher than the median for each bank characteristic, which includes liquidity ratio and Tier 1 capital ratio. Table 8 shows our results. We can see that banks with lower liquidity ratios (Column 1) further amplify the net Swiss franc asset revaluation effect on credit supply compare with banks with higher liquidity ratio. However, our results do not suggest that the net Swiss franc asset revaluation has a significant effect on banks with lower capital ratios. This leads us to think that the revaluation effect (direct exposure) mainly spreads the exchange rate shock to credit supply through a liquidity channel. When we Comparing two banks with similar exposure to Swiss franc corporate lending, we find that the bank with better capital ratio, indicated by a higher tier-one capital ratio (Column 3), can neutralize the negative liquidity shock to credit supply. Banks with lower liquidity ratios show a more significant decrease in their credit supply in 2015 (Column 4). This result suggests that the credit loss effect(indirect) after the exchange rate shock transmit to bank credit supply through both liquidity channel and binding the capital constraint.

7 The firm level impact of the bank lending channel

We have observed a significant variation in bank lending during the post-shock period, which 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 the firm-level. We are particularly interested in answering two questions: (1)

	(1) FE gm(loan)	(2) FE gm(loan)	(3) FE gm(loan)	(4) FE gm(loan)
DMismatch^f	0.183***	-0.117	0.189***	0.285***
	(0.051)	(0.188)	(0.042)	(0.063)
IDMismatch	-0.098***	-0.158***	-0.096***	-0.107***
	(0.021)	(0.030)	(0.024)	(0.035)
DMismatch^f Interacted with				
Liquidity ratio	0.014			
	(0.030)			
Tier 1 capital ratio		0.494**		
		(0.232)		
IDMismatch Interacted with				
Liquidity ratio			0.004	
			(0.030)	
Tier 1 capital ratio				-0.032
				(0.060)
Bank Controls	Yes	Yes	Yes	Yes
R^2	0.398	0.401	0.398	0.400
Number of observations	10,052	10,052	10,052	10,052
Firm Fixed effect	Yes	Yes	Yes	Yes
Bank type	Bank	Bank	Bank	Bank
Firm borrowing type	Multiple	Multiple	Multiple	Multiple

To investigate the transmission channels of direct and indirect Swiss franc mismatch exposures through banks' balance sheets, we modified regression equation 5.1 and examined one interaction of one bank characteristic with a mismatch exposure at a time. In this regression, the interacted bank characteristics are represented as dummy variables that take a value of one if the observation was higher than the median for each bank characteristic, which includes liquidity ratio and Tier 1 capital ratio. 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 headline 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

Can firms offset the bank-specific loan supply variation by set 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 headline results on 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[21][22]. In other words, we first generate fitted firm credit supply variations by using loan-level regression with non-standardized variables, then we standardize fitted firm-level variations and use them in firm-level regression.

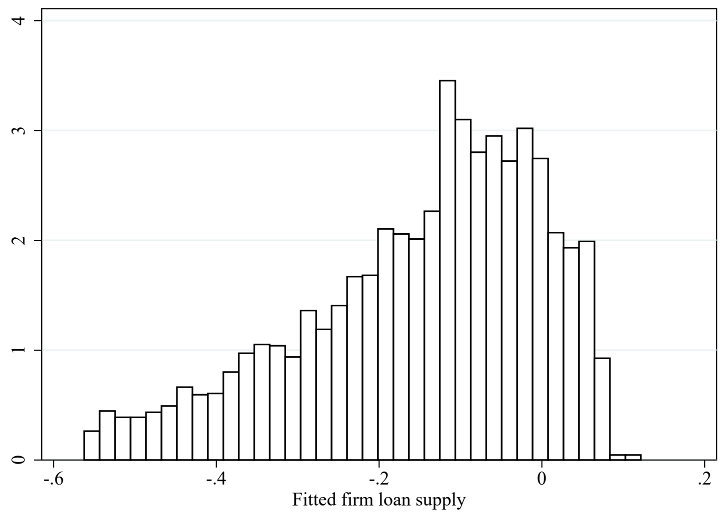


Figure 5: fitted firm-level credit supply effect

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[23].

[21] 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.

[22] 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.

[23] The fitted credit supply effect for both multi and single banks is presented in Appendix A.9.

	(1)	(2)	(3)	(4)
	OLS	OLS	OLS	OLS
	gm(total loan)	gm(total loan)	gm(total loan)	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 × 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 × 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

As discussed in section , we apply equation 5.4 to study the influence of the bank lending channel at the firm level. In order to tackle 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 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. This result 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 5.4, 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. However, the impact of credit supply becomes quite significant on firm investment when we analyze samples that include both multi and single-borrowing firms. From column (4), we find the coefficient is considerably larger 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 given total credit change could be that multi-borrowing firms tend to be larger in size and have better profitability and lower leverage (see 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 $\Delta supply_j^{AVE}$. [24] 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. 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 effect $\Delta supply_j^{AVE}$ impacts the likelihood of liquidation only in the sample that includes all firms, not in the sample exclusively comprising multi-borrowing firms. The significant coefficient on $\Delta supply_j^{AVE}$ in column (3) and (4), Panel B, reveals a negative relationship between credit supply vari-

[24] 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)
$\Delta supply_j^{AVE} \times$ log revenue		-0.014		0.029
		(0.011)		(0.021)
Fitted FE	Yes	Yes	Yes	Yes
R-squared	0.032	0.039		
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)
$\Delta supply_j^{AVE} \times$ log revenue		-0.017***		0.007
		(0.003)		(0.006)
Fitted FE	No	No	No	No
R-squared	0.060	0.061		
Number of observations	39,455	38,786	43,021	42,146
Bank controls	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes
Region $\times$ 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 $\times$ 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

ation and the possibility of liquidation, but only for small firms in the sample of all firms. Similar to the capital accumulation findings, a contractionary credit supply effect only increases the liquidation possibility for small firms. This further emphasize 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.

8 Conclusion

In conclusion, this study highlights the significance of exchange rate shocks in driving economic volatility in small open economies. While previous research has mainly focused on the indebtedness of foreign currency borrowers, our analysis demonstrates that exchange rate shocks can also impact local currency borrowers through the bank lending channel. Specifically, our findings reveal that direct and indirect currency mismatches on bank balance sheets are important determinants of post-shock bank lending and that banks' responses to exchange rate shocks can be heterogeneous and either contractionary or expansionary, depending on their balance sheet structure.

Our results have important policy implications. We provide empirical evidence supporting the need for macro-prudential policies to limit bank direct and indirect exposures to exchange rate risk. Such policies can help alleviate the adverse effects of exchange rate shocks on the real economy. Furthermore, our study underscores the importance of considering local currency borrowers in assessing foreign exchange risk in the 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.

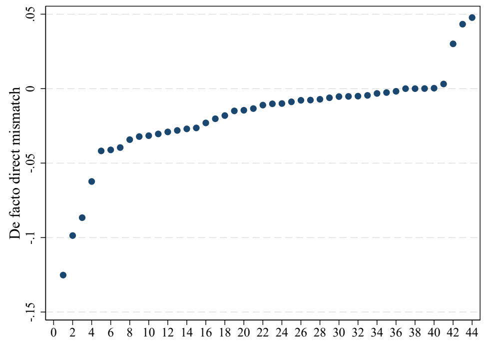
Table 12: Summary statistic mismatch

	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

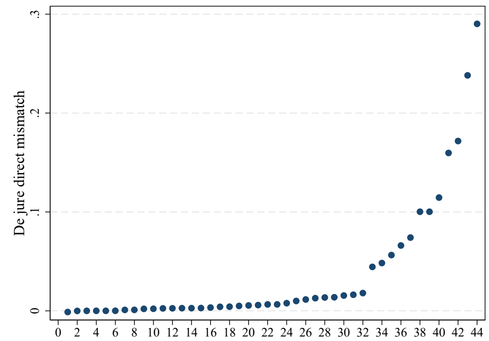
All mismatches are measured in 2014Q4 and expressed as ratio to the bank total asset value.

Table 13: Correlation among mismatch measurements

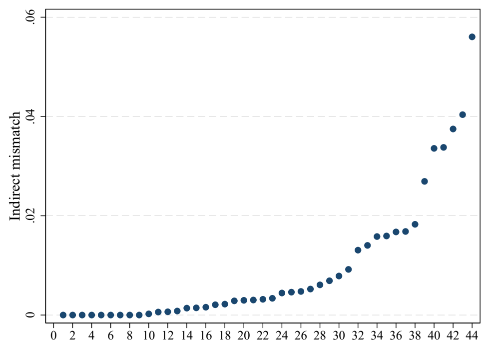
A.3 Distribution plots for mismatch measurements



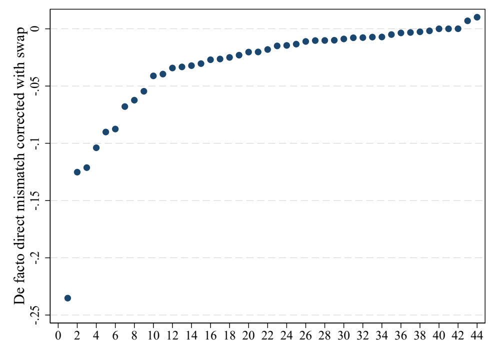
(a) *de facto* Direct mismatch



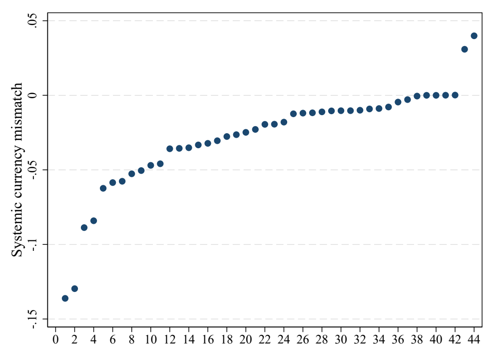
(b) *de jure* Direct mismatch



(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 uptick 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 volatility. 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

A.7 Parallel trends assumption for the systemic mismatch exposure

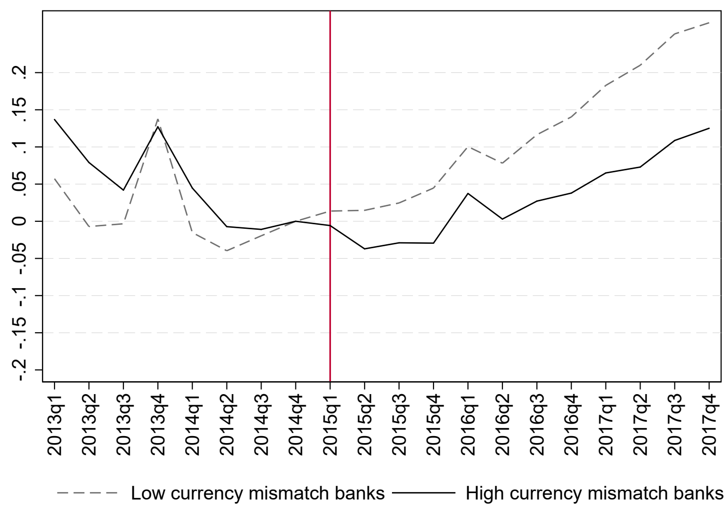


Figure 7: The bank lending channel at aggregate level

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 Results for the alternative specification

	(1)	(2)	(3)	(4)
	g(loan)	g(loan)	g(loan)	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 report several robustness test for alternative specification to capture quarterly variations The outcome variable is the log value of the loan volume between bank b and firm j in quarter t. The main independent variables are bank direct and indirect exposures to Swiss franc mismatches multiply the post shock dummy. Both direct and indirect exposures are not standardized. Standard Errors are clustered at bank level. *** denotes significance at the 1% level, ** at the 5%, and * at the 10%.

Table 17: The bank lending channel:quarterly difference in difference

A.9 Fitted firm-level credit supply for multi and single bank firms

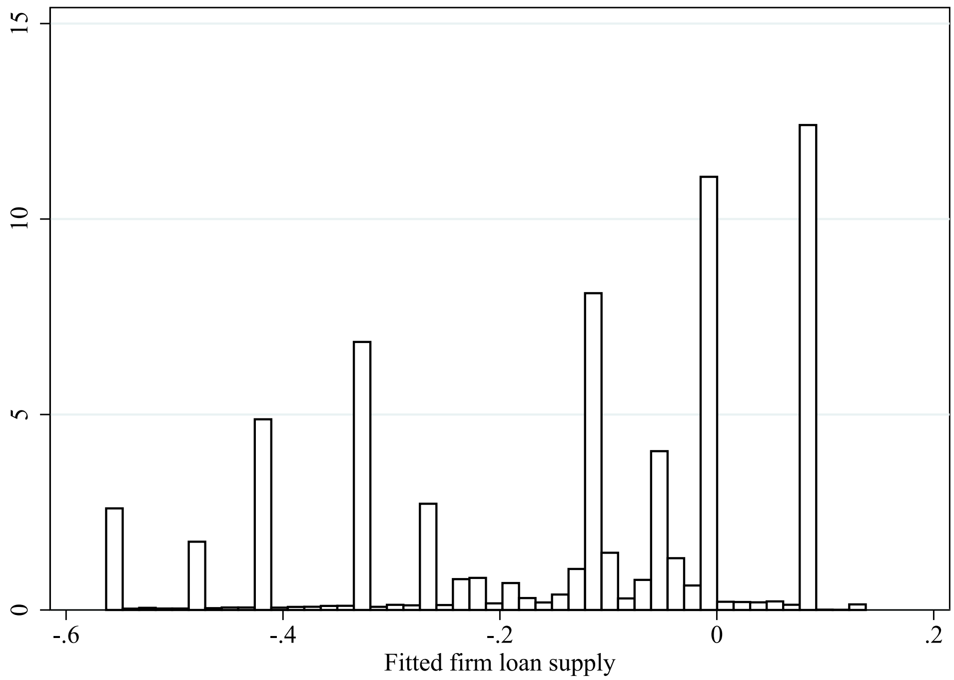


Figure 8: Fitted firm-level credit supply for multi and single bank firms

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.