Arbitraging Covered Interest-Rate Parity Deviations and Bank Lending

LORENA KELLER [a]

November 2023

I propose and test a new channel through which covered interest-rate parity (CIP) deviations can affect bank lending in emerging economies. I argue that when CIP deviations exist, banks attempt to arbitrage them. To do so, banks must borrow in a particular currency. When this currency is scarce, bank lending in the currency required to arbitrage decreases, while they use this currency in their arbitrage activities. I test this channel by exploiting differences in the abilities of Peruvian banks to arbitrage CIP deviations. I find evidence that supports the proposed channel.

[a]Keller: The Wharton School, University of Pennsylvania. Email: lorenak@wharton.upenn.edu. I am indebted to the Peruvian Superintendencia de Banca y Seguros (SBS, the Peruvian bank regulator) and the Superintendencia Nacional de Administración Tributaria (SUNAT, the Peruvian tax agency) for their collaboration in collecting and providing the data. I am very grateful to Lucas Cisneros, Aldo Delgado, Santiago Medina and Jorge Orozco for excellent research assistance. This project has greatly benefited from helpful comments from Manuel Amador, Jules van Binsberger, Aldo Delgado, Andres Drenik, Wenxin Du, Umang Khetan, Borja Larrain, Santiago Medina, Michael Roberts, Nikolai Roussanov, and Adrien Verdelhan, as well as seminar participants at Barcelona Summer Forum, BFI, Central Bank of Chile workshop, FMA, George Washington University, IMF, Indiana University, NYU Stern, Oklahoma University, University of Texas at Austin, Wharton, Wisconsin-Madison, NBER Summer Institute (International Asset Pricing), SED, Trinity College Dublin (ITM-International Macro), Rome Junior Finance Conference, and WFA. I am thankful for the financial support from the Jacobs Levy Equity Management Center for Quantitative Financial Research, Wharton's Dean Research Fund, and Wharton's Global Initiatives Research Program. All errors are my own.

1 Introduction

The covered interest-rate parity (CIP) condition is the fundamental pricing equation for foreign exchange-rate forward and swap contracts. Deviations from CIP occur in developing and developed nations alike, but for different reasons and with a different dynamic. Research has focused mostly on understanding how these deviations from CIP affect asset prices or in which environments they arise. However, not much is known about possible channels through which these deviations could end up affecting households and firms.

In this paper, I argue that CIP deviations could have broader effects than previously known. I show that, in an emerging-market setting, when banks arbitrage these deviations, they change the currency composition of their lending. This is important for the real economy. The literature has extensively demonstrated that firms' and households' currency mismatches, led by the currency composition of their debt, have serious effects on economic activity after a local currency depreciation. This paper complements the existing research on currency mismatches by suggesting that CIP deviations can have real effects and showing that CIP deviations can impact these mismatches through changes in bank lending.

I start by proposing a channel through which CIP deviations can affect bank lending in a partially dollarized economy. The channel works as follows. CIP deviations imply that arbitrage opportunities exist. When these deviations exist, banks (the natural CIP deviation arbitrageurs) attempt to arbitrage them.[1] However, the arbitrage requires banks to borrow a particular currency. When that particular currency is scarce, banks need either to increase rates paid on deposits or to shrink the amount of that currency being used in other activities, such as lending, in order to use these funds to arbitrage. Then either because of an increase in rates in the currency required to arbitrage or because of limited funds, lending in the currency needed to arbitrage will likely decrease relative to the one that is not required. Hence, arbitraging CIP deviations can contribute to changes in currency mismatches in partially dollarized economies.

[1] Banks cannot arbitrage them fully, or else CIP deviations would not exist.

I test this channel by studying the relationship between arbitraging CIP deviations and bank lending in Peru during an eight-year period from 2005 to 2013, excluding the Global Financial Crisis (GFC). I proceed in three complementary steps. First, I show that banks' exchange-rate and money-market transactions suggest that they arbitrage CIP deviations. Second, I show banks' funding in the currency required to arbitrage CIP deviations becomes scarcer or more expensive as CIP deviations increase. Third, I exploit that banks have different arbitrage sensitivities to CIP deviations to show that banks that arbitrage more shift their lending currency more, depending on what is profitable to arbitrage. This last step is where the main contribution of this paper lies.[2]

How is CIP arbitrage executed? Consider a local bank in Peru that has the opportunity to lend 1-month at the risk-free rate in dollars or in *soles*, the Peruvian currency. Under CIP, the return on lending soles directly should equal the return on lending dollars and simultaneously hedge the exchange-rate risk by selling dollars forward to convert them back to soles. The return of the combination of lending dollars and hedging the exchange-rate is the *soles synthetic rate*. The soles synthetic rate minus the soles cash rate is the *cross-currency basis*. The cross-currency basis measures the deviations from CIP.

Based on this description of how CIP is done, step one of my empirical analysis uses confidential data from Peru to show that banks' transactions are consistent with arbitraging CIP.[3] The data include all of the forward contracts of all banks in Peru and all of their daily spot transactions, as well as the banks' interbank loans, financial obligations, and investments. With this data, I show that consistent with the arbitrage, when the cross-currency basis increases and the soles synthetic rate is greater than the soles cash rate, banks borrow at the lower soles cash rate and lend at the higher soles synthetic rate. In practice, this involves four transactions: (i) borrowing soles, (ii) selling soles/buying dollars spot, (iii) lending those dollars, and (iv) hedging the exchange rate risk by selling dollars forward. The last three transactions correspond to the bank lending at the soles synthetic rate (buying dollars spot, then lending in dollars but hedging the exchange-rate risk). I

[2] Limitations of firm-level data and of a setting that allows for identification of real effects prevent me from analyzing effects at the firm level. However, there is no reason for the conclusions of the literature regarding real effects of currency mismatches not to apply to Peru. I discuss this later in more detail.

[3] As I describe later, an alternative explanation is that because banks hedge the exchange-rate exposure (Keller, 2020) and the hedging cost is measured by CIP deviations, banks make their lending decisions based on the hedging cost measured by CIP deviations.

show that both in the aggregate and at the bank level, the correlation between the cross-currency basis and each of these four transactions behaves as expected.

Arbitraging CIP deviations should not affect other markets, such as the credit market, if banks could easily fund the currencies required to do the arbitrage. But if the currencies banks need to fund the arbitrage are scarce when carrying out the arbitrage, there can be a pass-through to the lending market.

Hence, step two of my empirical analysis shows that the currency banks need to borrow for the arbitrage is scarce. To show the scarcity, I complement the analysis with confidential information about daily bank-level interest rates paid on bank deposits. With this data, I find that as the cross-currency basis increases, banks only pay higher deposit spreads and have lower liquidity on the currency that is required to arbitrage.

Therefore, given that banks seem to arbitrage CIP deviations but funding the currency required for the arbitrage is scarce, step three of my empirical analysis studies whether there are consequences in the lending market of banks doing the arbitrage in such conditions.

Step three relies on an important finding: I find that banks' transactions are consistent with arbitraging CIP deviations, but I also find that banks differ significantly in their response to these CIP deviations. I find that after a 1-percentage-point increase in the USDPEN cross-currency basis, some banks respond by allocating approximately 4% more of their assets to arbitrage, while others barely respond.

The finding that banks differ in arbitrage sensitivity derives from two computations. First, I compute a proxy for each bank's arbitrage position, which is the amount of a bank's forward position that is matched with a spot position in opposite direction. I use this proxy because every arbitrage transaction requires banks to offset their forward position with spot positions of similar magnitude. To prevent the results from being affected by banks' size, I scale each bank's arbitrage position by their assets. I call the resulting variable *"Matched/Assets."* Second, I regress the "Matched/Assets" variable on the cross-currency basis for each bank. The resulting coefficient, $\hat{\beta}_b$, is the arbitrage sensitivity, or in other words, the amount banks change their arbitrage positions after a change in the cross-currency basis. I find that banks differ significantly in their arbitrage sensitivity.[4]

To analyze the impact of arbitraging CIP deviations on bank lending in soles and dollars, I use (a) the bank-specific measure of banks' sensitivities to arbitrage CIP deviations, $\hat{\beta}$; and (b) the Chilean and Mexican cross-currency basis as an instrument for Peru's cross-currency basis (USDPEN). The heterogeneity in banks' arbitrage sensitivities to CIP deviations allows me to use a within-firm-month analysis. The instrument for Peru's basis allows me to reduce the influence of shocks to the Peruvian economy that correlate with CIP deviations in Peru and bank lending. It also allows me to mitigate concerns that the particular hedging choices of banks affect the cross-currency basis and, hence, the effects of such hedging on my results.

Making use of banks' differences in arbitrage sensitivities and of the instrument, I show that banks that allocate 1-percentage-point more of their assets to arbitraging CIP deviations increase their dollar lending relative to soles lending between 11% and 40% after a 1-percentage-point increase in the USDPEN cross-currency basis instrument.[5] This increase in the difference between dollars and soles lending is due to both an increase in dollars lending and a decrease in soles lending. These results stem from simultaneously comparing (a) lending of the same bank to the same firm at different levels of CIP deviations and (b) lending to the same firms in the same month of high-arbitrage banks relative to low-arbitrage ones.

Comparing lending across banks with different arbitrage abilities is one of the ways I alleviate the endogeneity problems that arise when trying to link arbitraging CIP deviations to bank lending. Because CIP deviations are endogenous, they correlate with macroeconomic variables that can affect lending in different currencies by other means that might not relate to arbitraging CIP deviations. Comparing how banks with different arbitrage abilities change their lending to the same firm in the same month controls for changes in economic conditions that affect all banks.

[4] I show that the heterogeneity in arbitrage sensitivity is associated with the type of bank customer. Banks with customers whose exchange-rate forward goes against the market's forward flows, arbitrage the most. These banks likely have larger arbitrage positions because they know that if they need to unwind their forward positions later on, they can do so with less price impact.

[5] This is, log(USD)-log(PEN). The most conservative estimate I obtained is 11%, which holds when restricting the sample to firms borrowing in soles and dollars. When including all firms and the possibility of firms switching currencies, the estimates increase to 40%.

However, banks are heterogeneous and therefore shocks might not affect them to the same degree. I take three steps to mitigate this problem. First, I use lagged bank controls to control for bank heterogeneity in their balance sheets.[6] Second, I provide robustness checks that narrow the analysis to banks that are similar in most respects. In this subset of banks, I analyze whether those that arbitrage more lend more in dollars and less in soles as the cross-currency basis increases. I find this is still the case. Third, I focus on whether correlations exist between the macroeconomic factors and CIP deviations that can affect the results. For brevity, I center my analysis on the most important correlation, that between the exchange-rate and CIP deviations (Avdjiev, Du, Koch, and Shin, 2019). I find that this correlation is not the one behind the results related to bank lending. In Online Appendix B, I also show that the institutional setting and exchange-rate-related policies are not affecting my results. I also discuss how the institutional setting in Peru applies more generally to other emerging economies.

My results are robust to a series of alternative specifications, such as using alternative measures of CIP deviations, using alternative samples and firms, and using alternative exposure measures to sort banks by arbitrage intensity.

To the best of my knowledge, this is the first paper to propose and empirically test a channel through which, by arbitraging CIP deviations, banks can change the currency composition of their lending portfolios. In this channel, I show that when banks arbitrage, they face liquidity constraints in the currency they leverage to arbitrage the deviations. Consequently, when engaging in the arbitrage, they reduce lending of the currency they leverage for arbitrage. Instead, they increase lending in the currency that they would have in excess after the arbitrage.

While I focus on a partially dollarized economy, it is likely that the contributions of this paper extend to other economies. Many countries where local banks do not actively take foreign currency deposits from local households and firms have important shares of foreign currency loans. The IMF's Financial Soundness Indicator lists several countries with more than 30% of foreign currency loans, including Canada, Luxembourg, United Kingdom, Singapore, and Switzerland. Given that global banks borrow and lend in various economies, arbitraging CIP deviations could affect the allocation of global banks' currency portfolios (and respective borrowing and lending)

[6]The results with and without bank controls are very similar.

across countries. Therefore, the mechanism outlined in this paper could apply on an international scale.

This paper complements three areas of research relative to current literature: CIP deviations, the effects of currency mismatches on the real economy, and understanding internal capital markets in the banking system.

First, my paper complements the current literature on CIP deviations by providing evidence that suggests that CIP deviations affect more than just arbitrage activities; they can also affect firms and households through changes in the currency composition of their loans.[7] This is novel in the literature of CIP deviations, which has mainly addressed the predominance of CIP deviations after the GFC (Baba, Packer, and Nagano (2008); Baba and Packer (2009); Coffey, Hrung, and Sarkar (2009); Mancini-Griffoli and Ranaldo (2011); Du, Tepper, and Verdelhan (2018))[8] as well as addressed why these deviations exist, what can be correlated with them, or environments in which these may appear (Borio, Iqbal, McCauley, McGuire, and Sushko (2018); Du, Tepper, and Verdelhan (2018); Avdjiev, Du, Koch, and Shin (2019); Wallen (2019); Correa, Du, and Liao (2020); Puriya and Brauning (2020); Rime, Schrimpf, and Syrstad (2020); Cenedese, Della Corte, and Wang (2021); Cerutti, Obstfeld, and Zhou (2021); Dedola, Georgiadis, Grab, and Mehl (2021); Aizenman, Ito, and Pasricha (2022); Du, Hebert, and Huber (2022); Liao and Zhang (2022a); De Leo, Gopinath, and Kalemli-Ozcan (2023); Cerruti and Zhou (2023)).[9] Except for a few papers such as Cerruti and Zhou (2023) and De Leo, Gopinath, and Kalemli-Ozcan (2023), most papers

[7]Two papers that have studied CIP deviations outside asset pricing are Ivashina, Scharfstein, and Stein (2015), who show that, if CIP deviations are allowed in equilibrium, a shock to European global banks' creditworthiness reduces their amount of loans in dollars, but not those in euros; and Amador, Bianchi, Bocola, and Perri (2020), who show that central banks' exchange-rate policy can be costlier when it conflicts with the zero lower bound and CIP deviations are allowed. In both studies, in contrast to my paper, the effects on the real economy are not *directly due to* arbitraging CIP deviations; rather, they result from shocks and policies in an environment where CIP deviations are allowed. Furthermore, the mechanism I propose is not related to shocks to the creditworthiness of banks or the zero lower bound.

[8]Akram et al. (2008) report that in developed countries, CIP deviations can be seen even before the GFC in high frequency but they are short-lived. However, most research renders these quite small at lower frequencies. In developing economies, these have been large, even before the GFC.

[9]Related to this literature are Gabaix and Maggiori (2015) and Gabaix and Koijen (2021). Gabaix and Maggiori (2015) study exchange-rate determination, an important ingredient in CIP computations. They highlight that exchange-rate is determined by the premium dealers charge to absorb demand-supply imbalances. Gabaix and Koijen (2021) predict that asset prices are determined by daily flows. In this context, Aldunante, Da, Larrain, Sialm, and Clemens (2022) use shocks to the flows in the spot market to document the effect on exchange-rate forwards and the corresponding elasticities in the Chilean market. Taking the spot and forward markets together, they argue that CIP deviations can exist if the price elasticity of spot and forward markets are not synchronized.

focus on developed economies. Because most of my sample exhibits carry trade inflows in Peru, my setting here resembles that in Keller (2020) and Amador, Bianchi, Bocola, and Perri (2020). In both cases, CIP deviations arise in a setting with capital inflows and a central bank that intervenes in the exchange rate to mitigate exchange-rate appreciation.[10]

Second, my paper complements the literature on the real effects of currency mismatches after depreciation shocks by showing that CIP deviations shift the currency in which firms borrow. In an environment with very limited hedging, which is the case in Peru (and also occurs in other countries (see, e.g., Alfaro, Calani, and Varela (2022), Levin-Konigsberg, Stein, Garcia Averell, and Lopez Castanon (2023)), firms and households' currency mismatches are typically caused by changes in the currency composition of debt. The literature shows that these mismatches have important effects on the real economy. Therefore, my paper suggests that CIP deviations could affect the real economy by showing that CIP deviations can affect these mismatches.[11]

More precisely, after a depreciation shock of the local currency, the effects on the real economy of currency mismatches include significant financial distress, reduced demand, increased unemployment, and worse recessions (Verner and Gyöngyösi (2020)). Firms with foreign currency debt also decrease investment and increase exit rates (Aguiar (2005); Kim et al. (2015); Hardy (2018); Verner and Gyöngyösi (2020); Du and Schreger (2022)). The effects are worse for smaller firms (Hardy (2018)) and for domestic-owned firms amid a currency and banking crisis (Kalemli-Ozcan et al. (2016)). However, before the depreciation shock, borrowing in dollars can relax financial constraints (Endresz and Harasztosi (2014); Rancière and Tornell (2016); Verner and Gyöngyösi (2020); Salomao and Varela (2021)).

I lack firm-level data and a setting that would allow me to identify the effects of the shift in the currency composition of firms' borrowing on their outcomes. However, these effects are likely present in Peru. For example, Humala (2019) finds that in Peru, the 30% depreciation of the sol

[10] Gutierrez, Ivashina, and Salomao (2023) study a different question using Peruvian data. However, their setting differs from mine. Their sample starts in 2012, and they cover a period characterized by a significant depreciation of the Peruvian sol and various regulations in the lending and forward markets that act as significant confounders for studying the effect of arbitraging CIP deviations on bank lending. To avoid such confounders, I end my sample period in 2013.

[11] I show that my results apply broadly, taking out firms with international trade and firms that hedge with derivatives. Jung (2023) shows that some firms with international trade hedge and that changes in the supply of hedging contracts can have important economic outcomes.

between 2013 and 2015 was associated with earnings losses of between 24% and 36%. Similarly, a survey by EY Peru[12] found that profits declined by between 15% to 20%, and that 75% of the firms in their sample were affected by the 10% depreciation of the sol in 2021.The Central Bank of Peru has said that the possibility of such negative effects has also shaped its regulations, including the de-dollarization regulation that occurred during the depreciation associated with the taper tantrum in 2013.

Third, my paper contributes to the literature on understanding of internal capital markets in the banking system by presenting new empirical evidence concerning how internal capital markets work for a bank that must allocate scarce currency-specific liquidity between its lending and trading divisions. The empirical evidence has mostly focused on diversified firms (Lamont (1997); Shin and Stulz (1998)), bank holding companies (Houston, James, and Marcus (1997); Houston and James (1998); Campello (2002); Ashcraft and Campello (2007); Cremers, Huang, and Sautner (2011)), and global banks (Cetorelli and Goldberg (2012a,b); Bruno and Shin (2014); Cao and Dinger (2022)). Evidence of reallocation of funds within a bank in a single country (Gilje, Loutskina, and Strahan (2016); Ben-David, Palvia, and Spatt (2017); Slutzky, Villamizar-Villegas, and Williams (2020)) focuses on reallocation between branches in different geographical locations or shifts from one type of loan to another (Martin et al., 2021). In this paper, I study a different dimension of reallocation, that between business divisions and across different currencies.

This rest of this paper is organized into five sections. Section 2 reviews the CIP condition and how arbitraging works. Section 3 describes CIP deviations and the banking system in Peru. Section 4 describes the data. Section 5 presents the methodology and results. Section 6 concludes.

2 CIP Overview

This section looks at how CIP works and how arbitraging CIP deviations is done. It also introduces definitions I use throughout the paper.

[12] I do not have access to the survey, but the consulting firm shared those results in the press (see Gestion, *"Tres de cada cuatro empresas fueron afectadas por disparada del dolar"* (January 5, 2022) at: https://gestion.pe/tu-dinero/tres-de-cada-cuatro-empresas-fueron-afectadas-por-disparada-del-dolar-noticia/).

CIP is a nonarbitrage condition. It states that an investor should be indifferent between the following two lending strategies: lend a particular currency directly (i.e., in the spot market, money-market, or cash market), or lend it synthetically. Lending soles directly is depicted in red in Figure 1, while lending soles synthetically is shown in blue. *Lending soles synthetically* involves lending dollars and hedging the exchange rate risk. The notes below the figure describe the details of each lending strategy and its returns.

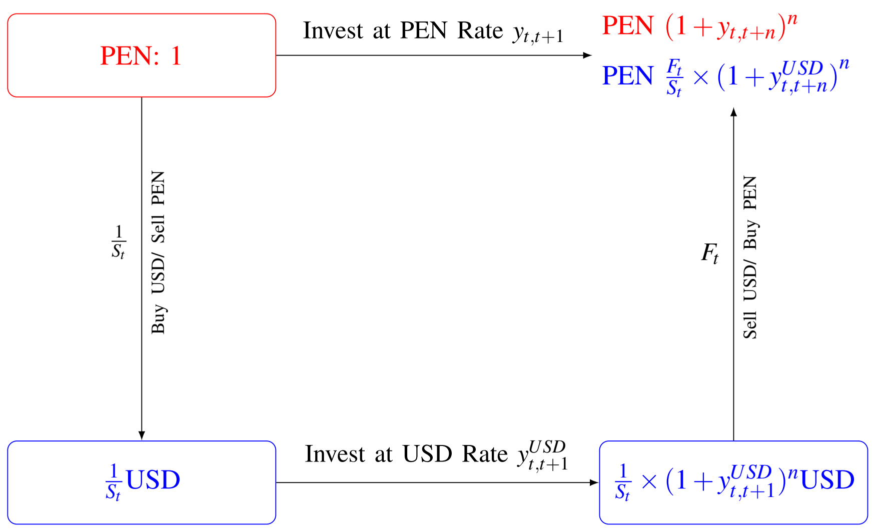

Figure 1: Example of Covered Interest-Rate Parity (CIP)

This figure shows an example of CIP. Here, an investor should be indifferent between two strategies. The first strategy, highlighted in red, is to lend 1 sol (PEN) directly in the spot market at the rate $y_{t,t+1}$. When the investor does this, at $t+1$ the investor will have PEN $1+y_{t,t+1}$. The second strategy, highlighted in blue, starts by using the PEN 1 that the investor has at time t and changing it for dollars (USD). Denoting the exchange rate as S_t PEN per USD, the investor will have USD $\frac{1}{S_t}$. The investor lends these USD directly at the USD rate of $y^{USD}_{t,t+1}$. Hence, as of $t+1$, the investor will receive $\frac{1}{S_t} \times (1+y_{t,t+1})$ dollars. CIP means that, as of time t, locking into a $t+1$ exchange rate to convert the USD return into PEN should give the same PEN as if these PEN were lent directly. The $t+1$ exchange rate at which the investor can lock into in period t is given by the forward exchange rate F_t. Using the F_t exchange rate (also quoted as soles per dollar) to convert the dollar loan proceeds to PEN, gives PEN $\frac{F_t}{S_t} \times (1+y^{USD}_{t,t+1})$. Therefore, under CIP, the soles returns of the red and blue strategies are the same: $1+y_{t,t+1} = \frac{F_t}{S_t} \times (1+y^{USD}_{t,t+1})$.

Denote the n-year annualized *soles (PEN) rate* as $y_{t,t+n}$, the n-year annualized *dollar (USD) rate* as $y^{\$}_{t,t+n}$, the *spot rate* at which the bank would buy dollars as S_t and the *forward rate* today at which the bank sells dollars forward at $t+n$ as $F_{t,t+n}$. With this notation, the figure above and its description explain how, under CIP, the proceeds at $t+n$ of lending soles directly equal the proceeds of lending soles synthetically:

$$(1+y_{t,t+n})^n = \underbrace{\frac{F_{t,t+n}}{S_t} \times (1+y^{\$}_{t,t+n})^n}_{(1+y^{fwd}_{t,t+n})^n} \tag{1}$$

For simplicity, I denote the yearly return of this second strategy as $y^{fwd}_{t,t+n}$. This is the *soles synthetic rate* (or forward-implied soles rate). From Equation (1), it follows that

$$y^{fwd}_{t,t+n} \equiv \left(\frac{F_{t,t+n}}{S_t}\right)^{1/n} \times (1+y^{\$}_{t,t+n}) - 1 \tag{2}$$

When there are deviations from CIP, Equation (1) does not hold and one lending strategy provides a higher payoff than the other. The difference between the payoffs is known as the *cross-currency basis*, $x_{t,t+n}$. In the literature, the cross-currency basis is typically defined in dollar terms: $x_{t,t+n} = y^{\$}_{t,t+n} - y^{\$,fwd}_{t,t+n}$. Because I draw my analysis in this paper from the Peruvian banks' perspective, I define the cross-currency basis in soles terms:

$$x_{t,t+n} = y^{fwd}_{t,t+n} - y_{t,t+n} \tag{3}$$

Online Appendix A shows that the definition of the cross-currency basis in dollar terms commonly used in the literature ($x_{t,t+n} = y^{\$}_{t,t+n} - y^{\$,fwd}_{t,t+n}$) is equivalent to Equation (3). I use the soles definition because I study CIP deviations from the Peruvian banks' perspectives. Note that by taking logs to Equation (3), the cross-currency basis can also be understood as the difference between the forward premium and the interest-rate differential between the soles and dollar money-market rates:

$$x_{t,t+n} = \underbrace{\frac{1}{n}(f_{t,t+n} - s_t)}_{\text{Fwd Premium}} - \underbrace{(y_{t,t+n} - y^{\$}_{t,t+n})}_{\text{Rate Differential}} \tag{4}$$

During my sample period, the cross-currency basis was mostly negative. This means that when local banks were arbitraging the CIP deviations, banks would be profiting by borrowing synthetic soles and lending them in the money-market. When banks borrow soles synthetically, they effectively borrow dollars in the money-market, and hedge the exchange-rate risk. Hence, arbitraging a negative basis consists of four specific transactions: (i) borrowing dollars in the cash market, (ii) converting these dollars to soles, (iii) lending in soles in the money-market while (iv) engaging in a forward contract that sells the soles loan proceeds the bank receives at $t+n$ to convert them to dollars. With the dollars the bank receives from the forward contract, the bank pays back the dollars it borrowed at time t in the money-market. What remains as profit, in terms of annualized return, is the cross-currency basis (in absolute terms).

Opposite transactions would be needed to arbitrage the cross-currency basis when it is positive. Such would have been the case out of my sample period, when the cross-currency basis increases. Moreover, because in this paper the regressions have the cross-currency basis as a variable, the coefficients are interpreted as an increase in the cross-currency basis. Therefore, transactions compatible with banks' arbitraging CIP deviations imply that banks (i) borrow soles in the money-market, (ii) convert these soles to dollars in the spot market, (iii) lend dollars in the money-market, (iv) sell the dollars they receive from the amount they lent in the forward market to repay their soles loan.

Intuitively, the sign of the cross-currency can be interpreted as relative scarcity of a currency. The scarce currency is that which the market wants to borrow but not lend. The cross-currency basis turns negative as the forward premium decreases below the rate differential. Such a case occurs if there is, for instance, too much dollar selling pressure from investors in the forward market and banks cannot easily absorb those flows. The selling of dollar forwards indicates that investors selling dollars to banks want to have a liability in dollars and an asset in soles. That is, these investors are borrowing dollars and lending soles using forwards. This means there is scarcity of dollars (investors want to borrow dollars) relative to soles (investors want to lend soles). If this pressure is high enough, the synthetic soles rate decreases beyond its soles cash rate. Note that this is equivalent to having the synthetic dollar rate increase beyond its dollar cash rate.[13]

[13] This last statement becomes clear when expressing the cross-currency basis in dollar terms (i.e., $x_{t,t+n} = y^{\$}_{t,t+n} - y^{\$,fwd}_{t,t+n}$). In dollar terms, this is equivalent to a scarcity of dollars. Investors who might not have access to the dollar cash rate are willing to borrow dollars in the soles swap market at a higher rate than the cash rate.

3 Setting

This section has three subsections. Section 3.1 describes the main banking system's business divisions, emphasizing how the trading division works. Section 3.2 describes the importance of foreign investors in the exchange-rate market. Section 3.3 shows the behavior of CIP deviations in Peru and its similarities with those in other emerging economies.

For brevity, I've placed additional description of the institutional framework and other exchange-rate related policies in Online Appendix B, which shows that these policies and institutional factors do not affect the results of the paper.

3.1 Banking System

The financial system in Peru is composed of 13 banks and other types of financial institutions.[14] The 13 banks concentrate more than 90% of the assets of the financial system. My results in this paper are independent of whether I include only the 13 banks or the whole financial system, but because of data limitations and differences in behavior, I focus on banks, analyzing the interplay between their two main business divisions: lending and trading.[15]

Among the largest four banks operating in Peru, two are domestic and two are branches of foreign banks. For foreign banks to be considered part of the financial system in Peru, they need to have a branch there. This branch would be subject to Peruvian regulation and would have to comply with the same regulatory standards as domestic banks. Regardless of their country of origin, I refer to all banks operating in Peru as "local banks."

The main business division of banks is household and commercial lending, which represents 62% of the banking system's assets. The banking system in Peru is partially dollarized. This means that banks borrow dollars and lend them to households and firms. This phenomenon occurs in various emerging economies and is not unique to Peru (see, e.g., Dalgic (2020); Montamat

[14]Examples include financial corporations, financial cooperatives known as "cajas," and leasing companies. These institutions are called "informal-oriented" banks in Carpio, Keller, and Tomarchio (2022).

[15] My sample also includes Deutsche Bank Peru, which traded only USDPEN and fixed income. However, Deutsche Bank does not lend to firms or households; therefore, because lending is key to my analysis, I drop it from my sample.

(2020); Gutierrez et al. (2023)). During the sample period, loan and deposit dollarization averaged 59% and 55%, respectively. However, the rest of the economy operates in soles. In Peru, I have verified that there is limited hedging (both naturally hedged and through derivatives, as in Alfaro et al. (2022)). In this setting, changes in the share and growth of dollar lending relative to soles has direct consequences in currency mismatches of firms and households.

The other important division is trading, which constitutes USDPEN exchange-rate markets and investments in fixed income. The exchange-rate market, which is at the center of this paper, comprises spot and forward markets. Banks are market makers in both of these exchange-rate markets. They have two natural advantages over banks that do not operate in Peru in arbitraging CIP deviations. One, these are the only banks that can trade spot transactions in the interbank market. Two, they are the only banks that can access the Central Bank's primary auctions for money-market instruments, which are key for trading.[16] Also, when purchasing Central Bank CDs in the secondary market, they were not subject to restrictions that applied only to foreign investors starting in 2008.

By regulation, banks can have only very limited exchange-rate risk.[17] Since exchange-rate risk is composed of both forward and spot transactions, the net of spot and forward transactions must be small relative to their equity. However, they can balance a flow in the forward market with one in the spot market and, hence, conduct the transactions required to arbitrage the CIP deviations.[18] Therefore, finding that banks' spot and forward transactions are consistent with arbitraging CIP deviations (shown in Section 5.1) could result from banks using CIP deviations to guide their decisions to hedge exchange-rate risk. More concretely, banks have exchange-rate risk due to having dollar deposits. To hedge this risk, banks have two options. One is to lend in the same currency as the one they borrow. The other is to hedge with forward contracts. When the basis is negative, banks have incentives to use the dollar deposits to lend in soles, while hedging by buying dollars forward (and the opposite when the basis is positive).

[16] The main money-market security in which banks can invest soles assets is the Central Bank's certificate of deposit (CD). This is paper (i.e., a security) issued by the Central Bank to withdraw soles liquidity from the market. Once the CD is issued in the primary market, it is tradable in the secondary market.

[17] This regulation is extremely common in emerging economies (see, e.g., Canta et al. (2007); Tobal (2018); Alfaro et al. (2022)).

[18] Limits on the total exchange-rate position are different than the limits on forward holdings studied in Keller (2020).

To understand which types of liabilities they use for funding and which they use to invest when unwinding forward contracts in the spot market, I interviewed traders in Peru and confirmed their responses with confidential data from their reports on asset and liability decomposition by tenors.[19]

Though interbank loans are the first source of funding for soles and dollars, and they determine the rates paid for other liabilities,[20] they represent only a small fraction of their overall short-term funding (see Table A.I of the Online Appendix). On the liability side, banks complement interbank borrowing with term deposits of institutional investors and large corporations, which have direct connections with the trading desk. On the asset side, credit is the most important category. However, because the trading desks are not in the household and commercial lending business, I leave out this category. Instead, the trading division invests in deposits at the Central Bank as well as in investment securities.

Soles deposits at the Central Bank are marginally larger than investments in soles CDs at the Central Bank, but only a fraction of them could be used for checking accounts. Therefore, I take soles CDs at the Central Bank as the relevant investment account to do the arbitrage when the arbitrage requires banks investing in soles cash. In contrast, banks do not have investments in dollars. Therefore, I take dollar deposits at the Central Bank as the main investment account to do the arbitrage, when the arbitrage requires banks to lend in dollars cash. Given this, later on I do robustness checks that use the rates of these sources of funding and investment to calculate CIP deviations at the bank level.

[19]Note that the balance sheets of banks do not separate trading from other activities. This makes it challenging to understand which rates are applicable when borrowing and investing for trading purposes, hence my need to interview traders. This is also why Equation (8) proxies for the arbitrage activity by analyzing spot and forward transactions of opposite directions in Section 5.1.

[20]This is suggested by regressions of 1-month term deposit spreads on interbank dollar spreads. For soles and dollars, the spreads are over the soles target rate and the Libor, respectively. Regressing these deposit spreads over the interbank spreads yields that a 1-percentage-point increase in the interbank dollar (soles) spread is associated with a 0.65-percentage-point increase (3.4519 percentage points) in the 1-month dollar (soles) deposit spread. Similar numbers are obtained when lagging the interbank spreads by 1 month.

3.2 Foreign Investors and the Exchange-Rate Market

To better understand banks' trading activities, this subsection analyzes banks' counterparties in the exchange-rate forward market. I focus on the forward market because I lack sufficient counterparty information for spot transactions.

I use the forward dataset to manually classify each counterparty in each forward transaction into broad counterparty-type categories. I find that foreign investors, who mostly trade nondeliverable forwards, are the banks' main counterparties in the forward market. Excluding interbank deals, foreigners account for nearly 60% of the traded volume. The 1-month maturity is the most-traded forward contract, accounting for 54% of all forwards traded. Accordingly, I use this maturity in my baseline analysis. I use other tenors in my robustness checks, and my results hold.

To arbitrage CIP deviations, banks must have a specific position in the forward market, and foreign investors on the opposite side are not going to arbitrage these deviations.

At this point, one might ask, why wouldn't foreign investors arbitrage CIP deviations? Why are they instead on the other side of trades?[21] There are two explanations for this: (a) market segmentation and (b) carry-trade motives.

First, as described in the previous subsection, market segmentation between foreign and local banks[22] sets foreign investors at a disadvantage relative to local banks when trading CIP deviations. Foreign investors do not have access to key money-market instruments and the interbank spot exchange-rate market that local banks access. Hence, their profitability when arbitraging CIP deviations is often lower than those obtained by local banks.

[21] Table A.IV in the Online Appendix shows the estimated correlation between the cross-currency basis and the share of dollars forward local banks buy, splitting the sample into foreign and local investors. When trading with foreign investors, a 1-percentage-point increase in the cross-currency basis is associated with a 2.3-percentage-point decrease in local banks' share of dollar purchases from foreign investors. With local investors, this result is a decrease of only -0.6 percentage points and not statistically significant. It is only weakly significant for the share in number of trades.

Because local banks need to sell dollars forward to arbitrage an increase in the cross-currency basis, the decrease in the share of dollar purchases from foreign investors is consistent with local banks arbitraging the cross-currency basis from foreign investors.

[22] See Online Appendix C for more information on the market segmentation.

Second, as I describe in the next subsection, CIP deviations were mostly negative during my sample period, during which banks' forward positions were mostly long dollars forward. Foreign investors were often selling dollars forward. In this setting, if foreign investors have a limited balance sheet to allocate to Peru, they could even prefer to do the carry trade by selling dollars forward rather than by purchasing dollars forward to arbitrage CIP deviations.

During my sample period, carry trade was particularly profitable. Because it involves getting a liability in a low interest-rate currency, which at this time was the dollar, and getting an asset in the high interest-rate currency, which at this time was the sol, foreign investors could decide to sell dollars forward to engage in the carry trade. Doing so directly gives them a liability in dollars and an asset in soles.[23] In line with this, I find that foreign investors' carry trade annualized returns were 6.17% while annualized arbitrage profits (computed with CIP deviations using the Libor over the same period) were 1.1%.[24]

3.3 CIP Deviations

Figure 2 plots the annualized cross-currency basis for 1-month contracts for the soles-dollar currency pair (USDPEN) and the average across other Latin American currency pairs between February 2005 and February 2013, excluding the Global Financial Crisis (GFC).[25]

There are three takeaways from Figure 2. First, these deviations are large in economic terms, even after considering bid-ask spreads. The average of the absolute value of the basis for USDPEN and other Latin American baskets is 0.60%, far greater than the 0.23% bid-ask spreads.[26] Second, the USDPEN cross-currency basis is closely correlated (above 0.4) to the cross-currency basis of

[23] This strategy could be preferred to a strategy of doing the carry trade by borrowing dollars and investing in soles short-term assets because of the high fees that apply to foreigners when purchasing the Central Bank CDs.

[24] To make these calculations comparable, I computed CIP deviations only when they were negative, since this is when carry trade is done. Within my sample period, this was starting in October 2007, excluding the GFC. I also used 1-month forwards and 1-month CIP deviations (annualized in both cases). To calculate carry trade profits of foreigners, I calculated the profitability of foreign investors' forward trades when they sold forward contracts, as this is likely the most common way foreigners do the carry trade (given the market segmentation).

[25] After February 2013, Peru began implementing regulations that affected both bank lending and the forward markets (see Online Appendix D). This makes it hard to analyze the effects of arbitraging CIP deviations on bank lending after that date, which is why I end the sample period there.

[26] In Peru, it has oscillated between -2% and 2% when excluding the GFC. Even after transaction costs, the cross-currency basis in Peru has also been above 1% in absolute value.

other Latin American countries. Finally, while the cross-currency basis switched signs during the sample period, when removing the GFC, the cross-currency basis was mostly negative (during the GFC, it was positive). As mentioned in Section 2, this means that on average, there was excess liquidity of the domestic currency or analogously, scarcity of dollar funding. In this context, Peruvian banks could profit from borrowing soles synthetically and lending them in the money-market. However, while the level of CIP deviations is on average negative during my sample period, the changes in cross-currency basis have been both positive and negative.[27]

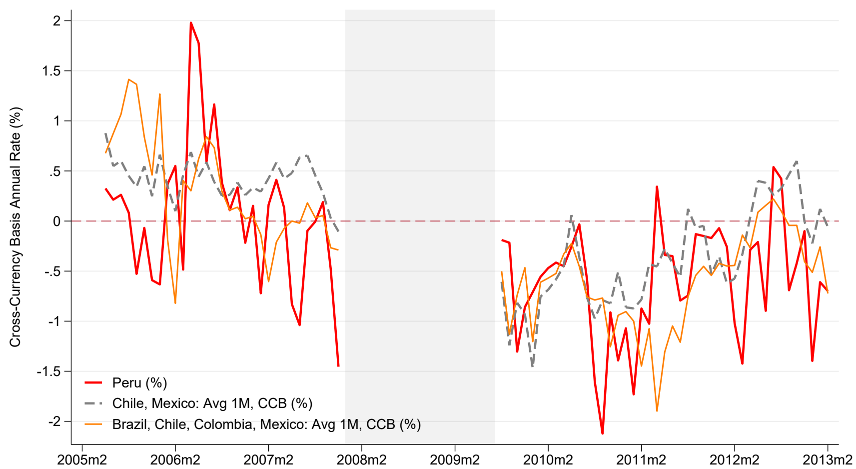

Figure 2: CIP Deviations in Peru and Other Latin American Countries

This figure plots the USDPEN cross-currency basis against the average of the cross-currency basis of other Latin American currency pairs across time. The orange line is the average of the cross-currency basis of Brazil, Chile, Colombia, and Mexico. The dotted gray line is the average of the cross-currency basis of Chile and Mexico. The red line is the cross-currency basis of Peru. Though the level of Peru's cross-currency basis is closer to the average of Brazil, Chile, Colombia, and Mexico, its movements are more correlated to those in Chile and Mexico. All of these cross-currency bases are computed using the local currency against the dollar, and they are all 1-month bases. The shaded gray area represents the GFC. I am not showing these months for two reasons: to prevent an outlier period from affecting the results, and because the significant deviations affect the scale, making it hard to understand the scale in normal times.

Likely, CIP deviations capture pressures coming from the forward market, the spot market, or the money-market. However, in Peru, three pieces of evidence suggest that the initial pressure seems to be coming from the forward market rather than the spot market. The spot and money-markets then adjust to possible reactions of banks and the Central Bank.[28] First, the Central Bank Inflation Reports commonly state that the exchange-rate movements are driven by flows of foreign

[27]Given that the regression coefficients analyze changes in the cross-currency basis and not the levels, the results discussed when interpreting the regression coefficients of the effects of an increase in the cross-currency basis also pertain to my sample.

[28]For instance, banks change their spot position to arbitrage these deviations, and the Central Bank can react to smooth exchange-rate volatility caused by changes in forward flows by intervening in the spot market.

investors in the forward market. Second, banks face investors' sales of dollar forwards when the sol appreciates and investors' purchases when the sol depreciates. This direction does not occur in the spot market. Third, the magnitude of the forward flows is typically three times as large as those in the spot market.

Then, analyzing the forward market, I find that banks' net long-forward positions, which capture demand-supply imbalances in the forward market, are strongly negatively correlated with CIP deviations ($\rho = -0.7064$). As previously described, foreign investors are key to driving the flows in this market. While the flows of foreign investors seem aligned with carry trade motives at times when they sell dollars forward, in general, these flows could represent hedging or speculative motives. The degree of each co-varies with global market conditions.

The importance of forward demand aligns with the conclusions drawn by Liao and Zhang (2022b), who emphasize that changes in the demand of dollar forwards to hedge currency risk are key to explaining CIP deviations. While CIP deviations could also reflect costs associated with absorbing imbalances in the forward market, I find that changes in the demand of forwards play a more important role.[29] Moreover, as shown in Figure 3, rates adjust to close the cross-currency basis, albeit they do not completely close the gap.

As discussed in Online Appendix C, market segmentation likely helps CIP deviations to capture shifts in demand. In a setting where banks have an advantage accessing the markets related to arbitraging CIP deviations, they can charge a markup when absorbing imbalances in the forward market. This can explain why CIP deviations existed even before the GFC and before any capital controls that could limit banks' absorption capacity.

4 Data

The sample period for my datasets is February 2005 through February 2013. The end date corresponds with the month in which the Central Bank of Peru began setting regulations that affected both my main outcome and my explanatory variables. These regulations are not related to Basel III;

[29] Results available upon request.

instead, they were designed to reduce dollarization, amid a significant depreciation that occurred after the taper tantrum. The regulations included both restrictions on bank lending in dollars (Amado, 2022) and restrictions on banks' forward transactions. These restrictions are explained in Online Appendix D. The results are robust to expanding the sample (see the last row of Table A.VI). Next, I describe the sources of data I use.

Market data. I obtained market-based data on foreign exchange and money-market data from Bloomberg. I also obtained local interbank rates from the central banks of Peru, Chile, and Mexico. I have used all of these to compute the cross-currency basis across various currency pairs. The summary statistics for the USDPEN cross-currency basis and other currency pairs are reported in Table A.II in the Online Appendix.

I use the interbank rates to compute the cross-currency basis because (a) traders mention they use these as a reference, (b) the interbank rates influence all other rates, and (c) unlike deposits, interbank loans are typically used only for trading. A 1-percentage-point increase in the soles interbank spread (interbank rate minus soles target rate) is associated with a 3-percentage-point increase in the 1-month term deposit spread, while a 1-percentage-point increase in the dollar interbank spread is associated with a 0.65-percentage-point increase in the 1-month term deposit spread.[30] In my private conversations with traders, they report using these rates as guidelines to price the cross-currency basis. However, as I explain later, I add various other confidential datasets (a) to understand which other rates can be used to fund CIP deviations and (b) to compute robustness checks of my results using alternative rates for the calculation of CIP deviations.

The interbank dollar rate reflects the Peruvian banks' cost of funding better than the Libor (see Figure 3). The dotted gray line shows the difference between the dollar interbank rate and the Libor. Starting in 2008, when the Central Bank imposed high reserve requirements on banks when borrowing short-term from abroad (including subsidiaries borrowing from the headquarters), the dollar interbank rate has deviated significantly from the Libor. When the cross-currency basis has been negative, the dollar interbank rate has been greater than the Libor. Therefore, as shown in Figure 3, using the dollar interbank rate yields significantly smaller deviations from cross-currency basis than the Libor, making profits from arbitraging CIP deviations shrink relative to

[30] Obtained from unreported regressions.

the counterfactual where rates would not have been affected. However, the deviations from CIP, even after accounting for the market reaction of rates, remain large.[31] Using the dollar interbank rate becomes less important relative to the Libor after 2013, when my sample period ends. This is because since 2013, CIP deviations in Peru have mostly been positive; in this case, soles liquidity is scarce (as I discuss in Section 5.2).

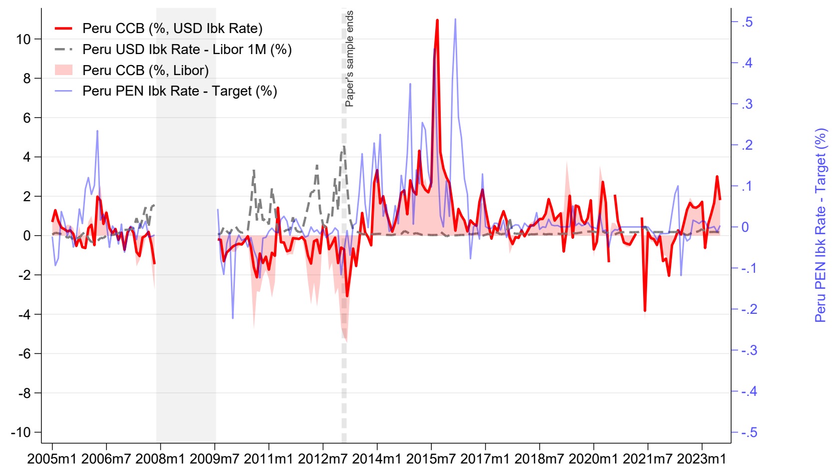

Figure 3: CIP Deviations and Interest-Rate Spreads

This figure plots Peru's cross-currency computed in two different ways and the interest-rate spreads for soles and dollars. The red shaded area shows the cross-currency basis computed using one-month Libor. The solid red line is the cross-currency basis computed using dollar interbank rates. I use line as the benchmark for my analysis in this paper. The dollar spread (the gray dotted line) equals the dollar interbank rate in Peru minus the one-month Libor. The blue line is the soles interbank spread, computed as the soles interbank rate minus the soles target rate of the Central Bank. For clarity, I plot the soles interbank spread on the right axis. The sample period is February 2005 to February 2013.

Bank-level data. I use bank-level data combined from a series of individual bank reports to Superintendencia de Banca y Seguros (SBS), the bank regulator. These reports are mandatory for all banks operating in Peru; most of them are confidential. The first report entails the universe of their forward contracts. With these contracts, I can compute the net long dollar forward position of a bank, i.e., the net long dollar position of all trades that are currently active (that have not expired). Precisely, the net long-dollar forward position of a bank at time t is

[31]The higher dollar interbank rate compared to the Libor is not due to risk aversion. Moreover, if there was risk aversion, one would expect the cross-currency basis to be positive. This would mean that foreign investors would require a higher soles synthetic rate as a return than the soles cash rate. However, they are willing to obtain a lower soles synthetic rate than the market during the time when the cross-currency basis is negative. In line with this, during these periods, the sovereign credit default swap was at its minimum and there were capital inflows. At that time, the higher dollar interbank rate thus seems to be related to the Central Bank's policies to mitigate the exchange-rate appreciation and inflows. These policies are explained in Online Appendix B. They do not impact my results.

$$\text{Fwd Pos}_t = \text{Fwd Pos}_{t-1} + \text{Fwd Buy}_t - \text{Fwd Sell}_t - (\text{Fwd Buy Exp.}_t - \text{Fwd Sell Exp.}_t)$$

where *Fwd Pos*$_t$ is the net long dollar forward position, *Fwd Buy*$_t$ are the forward dollar purchases, *Fwd Sell*$_t$ are the forward dollar sales, *Fwd Buy Exp.*$_t$ are the purchases of dollar forwards that expired, and *Fwd Sell Exp.*$_t$ are the sales of dollar forwards that expired. I verify that these positions equal those that are reported as forward positions in other confidential reports sent to the bank regulator.[32]

The second report contains their daily spot transactions.[33] The third report adds information on money-market positions. More specifically, in addition to using banks' public balance sheets, I use a third report that contains banks' daily positions on various money-market accounts, including interbank loans, financial obligations, investments in short-term assets, and liquidity ratios. This report does not include rates. I complement the money-market data with a fourth confidential report that includes banks' assets and liabilities split by maturity. This allows to me pin down which liabilities and investments are most likely to be used for arbitraging CIP deviations, and to provide various robustness checks accordingly.

I also build a dataset on funding and investment rates combining three other reports. For funding rates, I use a fifth confidential report that includes rates and balances on new deposits, split by deposit type. For investment rates in soles, I use a seventh dataset that includes monthly snapshots of all fixed-income holdings of banks. This dataset includes information on the security CUSIP, purchase date, currency, yield-to-maturity, and maturity of the securities. Importantly, it has the interest rates and date at which each bank bought the Central Banks' certificates of deposit. For investment rates in dollars, I use an eighth dataset that has the daily rates at which banks invest

[32] To verify that the computed *Fwd Pos*$_t$ corresponds to the reported ones, I took the initial input *Fwd Pos*$_0$ from the confidential reports.

[33] I have confirmed that the daily transactions are consistent with their reported forward and spot positions. Specifically, a bank's long-dollar spot position can be computed in two ways:

$$\text{Spot Pos.}_t \equiv \text{Spot Pos.}_{t-1} + \text{USD purchase}_t - \text{USD sale}_t \quad (5)$$

$$\equiv \text{USD Asset}_t - \text{USD Liab}_t \quad (6)$$

where Spot Pos$_t$ is the net long-dollar spot position, USD purchase$_t$ are the dollars purchased in spot, USD sale$_t$ are the dollars sold in spot, USD Asset$_t$ is the dollar assets, and USD Liab$_t$ is the dollar liabilities. The subscript refers to time. I have daily data for each bank's spot purchases and sales, and I have monthly data for each bank's assets and liabilities. I verify that at the end of the month, each bank's spot position computed by taking the previous month's spot position and adding all daily net dollar purchases (as in Equation (5)) equals the one computed by Equation (6).

dollars at the Central Bank; it also has daily interbank rates. I use the combination of funding and investment rates to build robustness checks using bank-level CIP deviations.[34]

Panel A of Table A.III in the Online Appendix shows the summary statistics of additional non-balance-sheet accounts, such as liquidity, profitability, and exchange-rate derivatives. The volume of exchange-rate derivatives are an important component of banks' balance sheets, representing nearly 20% of their assets. However, there is significant heterogeneity in the use of these derivatives. Some banks trade no exchange-rate forwards or swaps at all, while others trade extensively, where the trade volume represents more than 80% of their assets.[35]

This table also presents summary statistics of "net matched position" and $\hat{\beta}$, which are discussed in Section 5.1. "Net matched position" is the spot position that has been matched with the opposite transaction in the forward market. It takes a negative (positive) value when the position is a net short (long) dollar spot that is matched with net long (short) dollars forward. I use this variable as a proxy for the assets allocated to arbitraging CIP deviations. The $\hat{\beta}$ is the estimated sensitivity of assets allocated to arbitraging CIP deviations (scaled by assets) following a 1-percentage-point increase in the cross-currency basis. "Net matched position" and the estimation of $\hat{\beta}$ are described in Section 5.1.

Bank-firm-level data. The combination of the previous series of datasets, along with other tests, allows me to present evidence that banks seem to arbitrage CIP deviations, and that when doing so, they face scarcity of the currency required to arbitrage. To link these findings with bank lending, I also use the credit register collected by the SBS. It is the most granular dataset on bank loans; together with the spot and forward datasets, it is the main dataset I use in this paper.

This credit register, which is confidential, contains the monthly balances of all commercial loans outstanding in dollars and soles to firms that during the sample period had a loan outstanding of more than 300,000 soles (approximately $100,000) in aggregate.

[34] For various reasons described in Section 5.1, I cannot make these bank-level CIP deviations my baseline. However, my results are robust to using these rates.

[35] Interestingly, the three banks that most actively engaged in arbitrage are not the banks that were most affected by capital controls studied in Keller (2020).

The register contains almost 28,000 firms. Table A.III Panel B shows the summary statistics for these firms. "Small firms" have yearly sales below 20 million soles (approximately \$6.5 million), "medium firms" have yearly sales between 20 million and 200 million soles (\$6.5 million to \$65 million), and "large firms" have yearly sales above 200 million soles.[36]

5 Methodology and Results

This section studies the effect of arbitraging CIP deviations on bank lending. I proceed in three steps. In Section 5.1, I show that banks' money-market and exchange-rate transactions are consistent with arbitraging CIP deviations but that some banks arbitrage more than others. In Section 5.2, I show that banks face balance-sheet constraints when arbitraging these deviations, suggesting that arbitraging CIP deviations could be using resources that otherwise would have been used in lending. In Section 5.3, I provide evidence showing that arbitraging CIP deviations is associated with changes in lending.

5.1 Are Banks' Transactions Consistent With Arbitraging CIP Deviations? Are There Differences Across Banks?

To demonstrate that banks' money-market and exchange-rate transactions are consistent with arbitraging CIP deviations, I show that the correlations between CIP deviations and banks' exchange-rate and money-market transactions are statistically significant and have the expected signs. I do this both in the aggregate and at the bank level. I allow the strength of these correlations to be asymmetric depending on whether the cross-currency basis is positive or negative.

Since the arbitrage requires banks to borrow/lend a particular currency, we can expect that the coefficient on borrowing/lending in soles (dollars) would be particularly large if the arbitrage requires the bank to borrow/lend soles (dollars). For example, because the cross-currency basis is positive when the implied soles rate is higher than the soles cash rate, an arbitrageur is likely

[36] These correspond to the "medium", "large," and "corporate" categories that the SBS uses to classify firms.

to increase soles cash borrowing when the cross-currency basis is positive, compared to when the cross-currency basis is negative.

Equations (7a) and (7b), which are aggregate and bank-level estimations respectively, test whether banks' transactions are consistent with banks arbitraging the deviations:

$$y_t = \theta_0 + \theta_1 \text{CCB}_t \cdot \mathbf{1}(\text{CCB}_t > 0) + \theta_2 \text{CCB}_t \cdot \mathbf{1}(\text{CCB}_t \leq 0) + \varepsilon_t \tag{7a}$$

$$y_{bt} = \theta_0 + \theta_1 \text{CCB}_t \cdot \mathbf{1}(\text{CCB}_t > 0) + \theta_2 \text{CCB}_t \cdot \mathbf{1}(\text{CCB}_t \leq 0) + \text{Bank FE} + \varepsilon_{bt} \tag{7b}$$

In these equations, CCB_t is the USDPEN cross-currency basis and $\mathbf{1}(\cdot)$ is the indicator function. The dependent variables, y_t and y_{bt}, are money-market or exchange-rate positions, scaled by total assets. Money-market positions include interbank borrowing, obligations with financial institutions (two borrowing accounts that are more likely to be influenced by banks' demand of funds),[37] investing in the Central Bank's certificates of deposit (CDs) or sovereign debt, and investing in other bonds. Exchange-rate positions include spot and forward. y_t aggregates the data at the month level, while y_{bt} is at the bank-month level. Bank fixed effects ("Bank FE") are also present in the bank-level regression. The coefficients of interest, θ_1 and θ_2, capture the correlations between y_t and the cross-currency basis when it is positive and when it is negative, respectively.

Table 1 Panel A shows the expected results, split into three groups: borrowing, exchange-rate, and lending. As the cross-currency basis increases, borrowing soles and lending them synthetically becomes more profitable. In line with the arbitrage profitability, we see that banks (a) increase their borrowing in soles and (b) increase their lending of soles synthetically.[38] Asymmetry is also present and in the expected direction, in terms of both magnitude and statistical significance. When the cross-currency basis is positive, banks borrow more in soles than when it is negative. Banks also lend soles synthetically: (a) buy more dollars spot, (b) sell more dollars forward, and (c) invest more in dollars when the cross-currency basis is positive than when it is negative.

[37] This includes obligations with other nonbank financial institutions. For instance, it includes obligations with the Central Bank and financial institutions abroad.

[38] As per Section 2, lending soles synthetically means that banks lend in dollars but hedge the exchange-rate risk (i.e., they buy dollars spot to lend dollars in cash but sell dollars forward).

The magnitude of the spot and forward coefficients (Table 1, columns 5 and 6) are worth highlighting. In absolute terms, they are two to three times as large as those in the borrowing and lending sides. This means that banks are funding only part of their dollar purchases with new soles borrowed with interbank loans and financial obligations, as is the case with dollar borrowing when the cross-currency basis decreases. Accordingly, banks will need to fund their dollar purchases as the cross-currency basis increases through other sources, which can include reducing funding in different business divisions (i.e., previous investments as well as commercial and personal lending).

Shifting to the bank-level results, Panel B of Table 1 shows that the transactions are still consistent with arbitraging CIP deviations, but the results are less robust than the aggregate estimations. This is expected if banks' arbitraging activities are heterogeneous and not all banks arbitrage CIP deviations.

To further analyze the differences in banks' sensitivity to arbitrage CIP deviations, I compute bank-level sensitivities of the share of the banks' assets likely used to fund arbitrage after a change in the cross-currency basis. To do so, I first construct a bank-level measure that proxies for the share of a bank's assets invested in arbitraging the cross-currency basis. Then, I use this measure to compute bank-specific sensitivities.

Construction of the arbitrage proxy. To construct the proxy for the share of a bank's assets invested in arbitraging the cross-currency basis, I compute a daily measure of a bank's forward and swap positions that are offset by its spot position.[39] The amount of a bank's short forward position that is effectively matched with its long spot positions is the proxy. I call this variable the *matched position* of a bank. This measure can capture an arbitrage position because any CIP arbitrage position requires banks to offset their forward positions with spot positions. Although banks borrow and lend as part of arbitraging CIP deviations, I rely only on the exchange-rate

[39] I compute positions — that is, stock holdings rather than flows — for two reasons. First, I want to associate changes in the cross-currency basis with changes in these positions. This is given by the coefficient in the regression between these positions and the cross-currency basis. Second, because when a forward contract expires, a bank needs to renew it to keep its spot position hedged with the forward position. The purchases and sales of forward contracts could not be representative of whether a bank is arbitraging, as these could be due to renewals of expiration of forward contracts. In any case, because banks need to hedge their forward positions with their spot positions, when a bank decides not to renew a forward position, it will also need to change its spot position.

positions, because they are a cleaner proxy than the bank's use of the money-market.[40] Formally, I define the matched position of a bank as follows:

$$\text{Matched}_{bt} = \begin{cases} -\min\{|\text{Spot Pos.}|, |\text{Fwd+Swap Pos.}|\} & \text{, if Fwd+Swap Pos.} > 0 \land \text{Spot Pos.} < 0 \\ +\min\{|\text{Spot Pos.}|, |\text{Fwd+Swap Pos.}|\} & \text{, if Fwd+Swap Pos.} < 0 \land \text{Spot Pos.} > 0 \\ 0 & \text{, if sgn(Fwd+Swap Pos.)} = \text{sgn(Spot Pos.)} \end{cases} \tag{8}$$

Because the matched position of a bank ($Matched_{bt}$ in Equation (8)) is the amount of a bank's short dollar forward position that is offset with long dollar spot positions, it is computed as the minimum between the absolute value of the spot position and the forward position. $Matched_{bt}$ is negative when a bank has a net long dollar forward position that is offset and a net short dollar spot position (the first case in Equation (8)), and positive when the converse occurs (the second case). [41] When banks do not offset spot positions with forward positions, they are not arbitraging, so$Matched_{bt}$ is zero. The expected correlation between$Matched_{bt}$ and CIP deviations is positive. This is because when CIP deviations are positive, the arbitrage involves buying dollars spot and selling dollars forward (i.e., positive "Matched$_{bt}$").[42]

Computation of bank-specific sensitivities. I use$Matched_{bt}$ to estimate β, the measure I use to compare banks' sensitivities to arbitrage. I estimate β separately for each bank by using the

[40]Identifying a set of money-market accounts as a measure of arbitrage activity that is valid across banks and through time is challenging. For example, divesting liquid soles assets can be equivalent to borrowing soles at a very low rate. This can vary endogenously through time and across banks. Furthermore, the investment leg could be carried out with other less-traditional assets such as lending to the local corporate or household sector. Thus, there is a higher degree of uncertainty on which accounts are used for the borrowing and investing legs of arbitrage. On the other hand, the use of the exchange-rate market is unavoidable when arbitraging CIP deviations, as the bank has to swap currencies and hedge the operation. Such actions will always be reflected in the matched position of a bank. It is no coincidence that both the spot and forward+swap positions of banks have the strongest, most robust correlation with the cross-currency basis in Table 1.

[41]In this case, the bank has a net short dollar forward position (*Fwd+Swap Pos.*<0) and a net long dollar spot position (*Spot Pos.*>0). Analogously, it is matching its short forward and long spot positions by an amount equal to the size of the smallest one. This is the exact type of strategy that a bank executes when it arbitrages CIP and the cross-currency basis is positive, as arbitrage requires buying dollars spot and selling dollars forward.

[42]To see this, recall that when CIP deviations are positive, the soles synthetic rate is higher than the cash rate. Therefore, arbitraging CIP deviations involves banks lending at the soles synthetic rate and borrowing at the soles cash rate. Since lending soles synthetically involves banks lending dollars and hedging the exchange-rate, banks need to buy dollars spot and sell dollars forward to do the hedge.

following time-series regression:

$$\left(\frac{\text{Matched}}{\text{Assets}}\right)_{bt} = \alpha_b + \beta_b \text{CCB}_t + \varepsilon_{bt} \qquad \forall b \in B \tag{9}$$

where t indexes months, b indexes a particular bank, and B is the set of all banks in the sample. Month-level variables were calculated as the averages of their daily counterparts.

Because $\hat{\beta}$ measures the correlation between $Matched_{bt}$ and the cross-currency basis, we expect this coefficient to be positive when banks arbitrage CIP deviations. Indeed, as shown in Figure 4 (which plots the aggregate matched position of the banking system scaled by total assets against the cross-currency basis), the aggregate matched position of the banking system is highly positively correlated with the cross-currency basis. During the sample period, the correlation between these two series is 0.70.

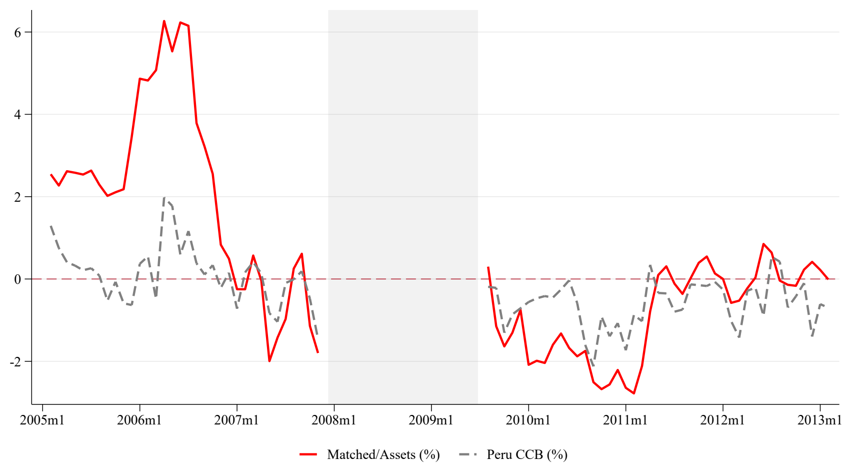

Figure 4: CIP Deviations and Matched/Assets

This figure plots Peru's cross-currency basis juxtaposed with a proxy of the share of assets allocated to arbitraging such deviations, "Matched/Assets," for the total Peruvian banking system. The sample period is February 2005 to February 2013.

At the bank level, we should observe that $\hat{\beta}_1 > \hat{\beta}_2 > 0$ if Bank 1 pursues a more aggressive arbitrage strategy than Bank 2. In this case, Bank 1 matches a higher percentage of its assets in the direction predicted by arbitrage when the cross-currency basis changes by 1 percentage point. Consequently, I interpret the estimated $\hat{\beta}_b$ coefficient as proxy of bank b's intensity of arbitrage sensitivities/activities.

Estimating Equation (9) separately for each bank yields considerable heterogeneity in the resulting coefficients. Although confidentiality agreements prevent me from showing the regression results for each bank, Figure 5 shows the smoothed distribution of the coefficients. A concentration of banks shows near-zero $\hat{\beta}$s (low-arbitrage banks), whereas another group of banks has $\hat{\beta}$s that are much larger than or significantly different from zero (high-arbitrage banks). The estimated coefficients of the low- and high-arbitrage banks lie in approximate ranges of [0, 0.2] and [1.6, 4.8], respectively.

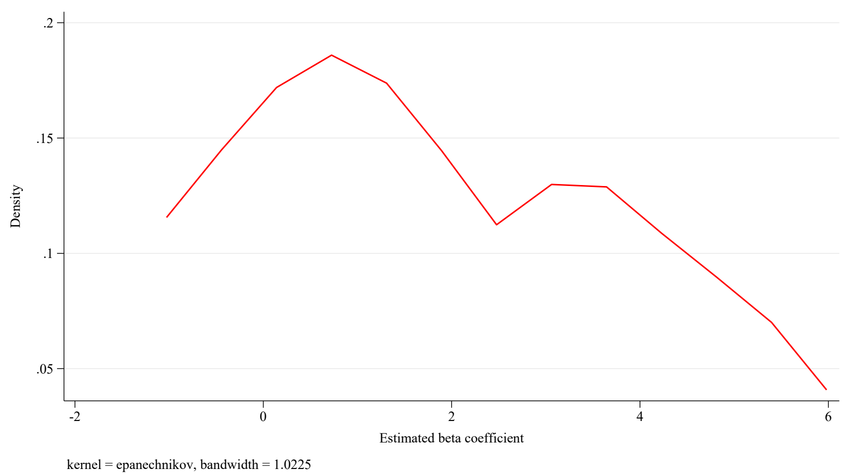

Figure 5: Smoothed Density of the Estimated $\hat{\beta}$ Coefficients

This figure shows the smoothed distribution of the coefficients. Due to confidentiality agreements, individual regression results are not shown.

I verify that $\hat{\beta}$s effectively capture arbitrage sensitivity. The exchange-rate and money-market transactions of banks that arbitrage more (higher $\hat{\beta}$) are more consistent with arbitraging CIP deviations than those that arbitrage less. Panels C and D in Table 1 show the results of splitting high- from low-arbitrage banks and estimating the same regressions as those in Panel B for each group. As expected, the estimated coefficients for the arbitrage accounts are larger in the group of high-arbitrage banks than they are in the low-arbitrage group. Specifically, the coefficients for high-arbitrage banks (Panel C) are, generally, very consistent with banks that are using these accounts for arbitrage, in terms of sign, significance, *and* asymmetry. However, the coefficients for the low-arbitrage banks (Panel D), are either (a) opposite to arbitrage, or (b) nonsignificant, or

(c) smaller than their counterparts from Panel C. These findings provide evidence suggesting that $\hat{\beta}$s proxy banks' arbitrage activity well.

Explanations for arbitrage heterogeneity. An underlying question is why some banks are able to arbitrage more than others. Online Appendix E addresses this question by providing correlations to show suggestive evidence of potential explanations. This analysis, however, has an important limitation: explaining the cross-section of banks is difficult because there are few banks.

With this caveat in mind, Online Appendix E evaluates two groups of possibilities. The first is that some banks can arbitrage more than others because they have fewer balance-sheet constraints. The second is that banks that arbitrage more do so because they can more easily unwind positions in the forward market. This can happen when banks that arbitrage more are those that have a greater set of clients, with flows that offset the trends in the forward market.

In sum, it seems that differences in banks' arbitrage sensitivities could be explained by their client heterogeneity. Banks arbitrage more when they can count on their clients to help them unwind positions. I also find that banks that arbitrage more have higher liquid assets; however, in line with balance-sheet constraints explaining part of the heterogeneity, making conclusions about the relationship between such constraints and arbitrage is difficult, because the analysis is subject to important reverse-causality concerns.

5.2 Is the Currency Needed to Arbitrage CIP Deviations Scarce?

Section 5.1 shows that banks' transactions are consistent with arbitraging CIP deviations. This section examines whether the currency that banks need to borrow to arbitrage is scarce when CIP deviations exist. If this is the case, banks are allocating a scarce resource to arbitraging CIP deviations. Therefore, the arbitrage can affect funding of that currency in other business divisions, such as commercial lending.

For example, consider that the cross-currency basis is positive. Because this implies that the soles synthetic rate is higher than the soles cash rate, arbitraging these deviations means having to borrow soles cash. Banks can source funds internally or externally. On one hand, if banks choose to source funds internally, they will be reallocating soles away from other divisions, such as the lending division. If so, soles lending falls. On the other hand, if banks source externally, they need to pay more to borrow soles. The likely result is higher soles lending rates, which may induce firms to substitute their soles borrowing for dollar borrowing. The converse happens when the cross-currency basis is negative.[43]

One indication that the currency required to arbitrage can be scarce involves analyzing what happens to the soles and dollar interbank spreads (with respect to the target rate) when the cross-currency basis is positive in contrast to when it is negative. Figure 3 (Page 21) shows that the soles interbank rate increases above the Central Bank's target rate when the cross-currency basis is positive and arbitraging CIP deviations requires banks to borrow soles. Similarly, the dollar interbank rate increases above the Libor when the cross-currency basis is negative and arbitraging CIP deviations requires banks to borrow dollars. The positive correlation between the cross-currency basis and the soles spread — as well as the negative correlation between the basis and the dollar spread — occurs despite the CIP deviations having already been computed with interbank soles and dollar rates. Therefore, although these changes in interbank rates reduce the cross-currency basis gap, the CIP deviations are much larger than the changes in rates. Figure 3 plots these correlations through 2023; it shows that these correlations hold generally.

More formally, to present evidence that banks seem to face borrowing constraints in the currency required to arbitrage, I replicate the regressions of the previous section (Equations (7a) and (7b)) using interest-rate spreads[44] and liquidity ratios. Table 2 presents the results in three levels: aggregate, bank-level, and decomposed by high- and low-arbitrage banks.

[43] Unfortunately, I lack information about interest rates and tenor at the loan level to test whether the adjustment is through quantities or rates. Therefore, for the bank-lending results in Section 5.3, I can use only quantities. However, quantities may just be reflecting worse rates in one currency versus the other. Because client portfolios (and hence client risk) can differ from bank to bank and loans could have various tenors, it is hard to assess the rate adjustment without loan-level rates.

[44] I use interest-rate spreads rather than the monetary-policy target rate so as not to pick up changes in monetary policy. For soles rates, I use the spread with respect to the Peruvian Central Bank's target rate. For dollar rates, I use the spread with respect to the Fed's target rate. Using the spread with respect to the Libor yields similar results. I compute this spread for two sources of financing that are likely used for arbitrage: new term deposits and interbank loans. Although I use interbank rates to compute CIP deviations — my private conversations with trading desks in Peru suggested these are the rates I should use to compute CIP deviations, because these are both borrowing and lending rates for banks — I have also done robustness checks using different rates, such as the Libor, risk-free rates computed by van Binsberger, Diamond, and Grotteria (2021), and deposit rates, among other variations (such as tenor). The results are robust to these changes in computation of the cross-currency basis.

The aggregate and bank-level results are similar: they show a scarcity of the currency required to arbitrage. A 1-percentage-point increase in the cross-currency basis is associated with a 0.3-percentage-point increase in the soles term deposit spread and a 3.1-percentage-point decrease in the share of soles liquid assets.[45] Analogously, a 1-percentage-point decrease in the cross-currency basis is associated with an increase of 0.43 to 0.56 percentage points in the dollar spread and a decrease of 1.51 to 4.41 percentage points in the share of dollar liquid assets.[46]

The demand for funds to arbitrage CIP deviations could explain the scarcity of the currency required to arbitrage, but CIP deviations might not be the main driver of these correlations — they correlate with other macroeconomic factors. For this reason, I do not claim causality.

Possible evidence for other factors affecting rates is that decomposing the bank-level regressions of Table 2 into high- and low-arbitrage banks (Panels C and D) shows that the estimated coefficients for the interest-rate spreads do not differ much between the two groups. This is likely because rates paid are determined in equilibrium and possibly due to factors other than arbitrage.

Having said that, the liquidity-ratio coefficients are notably larger and more significant for the high-arbitrage banks, whereas the low-arbitrage banks have nonsignificant coefficients that are also smaller in absolute value. This finding suggests that banks' arbitrage is driving part of these liquidity changes.

The origin of the scarcity of liquidity, however, is not relevant for this paper. What matters is that the currency required to arbitrage CIP deviations is scarce when banks want to arbitrage. This means that banks are optimizing under funding constraints: to arbitrage CIP deviations, they need to reallocate funds internally or pay more to obtain funds externally — either way can impact bank lending. I will address this in the next section.

[45]This ratio is a standard metric, used widely to assess whether banks can have liquidity to pay for new or past commitments. A decrease in this ratio means that banks will have less liquidity to use for new lending.

[46]Arbitraging CIP deviations is a direct channel that affects the share of liquid assets. It must involve buying a particular currency in spot, which mechanically affects liquid assets. For example, when the basis increases, the arbitrage involves buying dollars spot. Thus, banks are giving up cash in soles and receiving cash in dollars.

5.3 How Does Arbitraging CIP Deviations Affect Bank Lending in Soles and Dollars?

This section examines whether the arbitrage of CIP deviations in a context where the funding currency is scarce can affect bank lending in soles and in dollars.

Estimating the effect of arbitraging CIP deviations on bank lending is challenging, for three main reasons. First, CIP deviations are affected by macroeconomic shocks that affect CIP deviations and banks' decisions to lend in different currencies. Second, these macroeconomic shocks also affect firms' investment opportunities and thus their credit demand. Therefore, controlling for the effect of these shocks is crucial, both from the bank side and from the firm side. Third, banks' lending decisions themselves can affect CIP deviations. Given that banks operate in the exchange-rate and commercial lending markets, their actions affect both markets. A bank that decides to lend in a particular currency and simultaneously hedge the exchange-rate risk could change its demand in the forward market and ultimately affect the USDPEN cross-currency basis.

The main regression specification, shown in Equations (10a) and (10b), addresses these problems in three ways. First, it compares how banks with different sensitivities to arbitrage CIP deviations ($\hat{\beta}$) change their lending in dollars and soles following changes in the cross-currency basis. Then, as long as shocks affect all banks equally, banks' loan supply should not be affected by such shocks.

Second, it focuses only on firms with multiple bank relationships (more than 70% of my sample) and compares how banks with different sensitivities to arbitrage CIP deviations change their lending to the same firm in the same month. Performing a within-firm-month analysis (i.e., using firm-month fixed effects) and only comparing changes of bank lending to the same firm reduces concerns that the results could be driven by changes in firms' credit demand.

Third, it instruments the CIP deviations in Peru with those in Mexico and Chile. Using the cross-currency basis of Mexico and Chile as an instrumental variable (IV) not only reduces the influence of shocks to the Peruvian economy on the estimation results but also prevents the results from being biased by Peruvian banks' trading decisions in the exchange-rate market that affect the

USDPEN cross-currency basis. More precisely, I estimate the following baseline two-stage least squares model:

$$CCB^{\text{Peru}}_{t-1} \times \hat{\beta}_b = \gamma_0 + \gamma_1 \text{CCB}^{ChMex}_{t-1} \times \hat{\beta}_b + X'_{b,t-1}\Theta + \psi_b + \upsilon_{b,t-1} \tag{10a}$$

$$y_{bft} = \alpha_0 + \alpha_1 \widehat{CCB^{\text{Peru}}_{t-1} \times \hat{\beta}_b} + \psi_{bf} + \psi_{ft} + X'_{b,t-1}\Psi + \varepsilon_{bft} \tag{10b}$$

where y is the observed credit outcome (log of USD, PEN, total, and share of USD loans)[47] given by bank b to firm f on month t; CCB^{Peru}_{t-1} is the 1-month lagged cross-currency basis of USDPEN; CCB^{ChMex}_{t-1} is the average one-month lagged cross-currency basis of Chilean and Mexican peso against the dollar (USDCLP and USDMEX, respectively); $\hat{\beta}$ (estimated in Section 5.1) measures the bank arbitrage intensity level; $X_{b,t-1}$ is a vector of 1-month lagged bank controls; and ψ_b, ψ_{bf}, and ψ_{ft} refer to bank fixed effects, bank-firm fixed effects, and firm-month fixed effects, respectively. Equations (10a) and (10b) refer to the first and second stages of the model, respectively.

I use the average between the 1-month USDCLP and USDMEX cross-currency bases for two reasons. First, for the instrument to be valid, it must be highly correlated with the USDPEN cross-currency basis. The USDCLP and USDMEX cross-currency bases are the two Latin American currencies whose correlation with the USDPEN cross-currency basis is the strongest.[48] The average combined basis of USDCLP and USDMXN has a correlation of 0.54 with the USDPEN cross-currency basis. This is aligned with the first-stage results (presented below), suggesting there is not a weak-instrument problem. Second, Peruvian banks rarely trade these currencies and are

[47]For this regression, I sum across all types of loans for each bank-firm-month. Each observation includes only firms that have positive total credit with a bank. However, a firm could be borrowing only soles or only dollars at one point in time. To keep the same number of observations between soles and dollar loans and to avoid considering different samples of firms when looking at soles versus dollar loans, before taking logs I add 1 sol (approximately 0.33 dollars) to all loan balances. Moreover, to make loan balances compatible across time, the dollar loan balances use a constant exchange-rate as of the start of the sample, February 2005. I have also performed robustness checks where I do not add 1 sol to the loans. The conclusion remains, although the coefficients are smaller. Similarly, I have also done robustness checks without adjusting the exchange-rate to have a constant exchange-rate. The results remain.

[48] I evaluate within Latin America because while emerging economies' CIP deviations covary significantly with Peru, the closest are Latin American countries, and within that, USDCLP and USDMEX. This is natural when CIP deviations price the net demand of local currencies/dollars forward that banks need to absorb. In small open economies, foreign investors play an important role. Their demand for Latin American currencies is likely more correlated than in emerging economies in other regions that do not share as many similarities.

thus unlikely to affect their prices. Fewer than 1.1% of all of the forward contracts that banks in Peru traded were USDMXN or USDCLP.[49]

The role of the bank-firm fixed effects is to control for time-invariant characteristics between a bank and a firm. They also control for time-invariant differences across banks. This is important because shocks that correlate with CIP deviations may not affect all banks in the same way. If these shocks are also correlated with banks' sensitivities to arbitrage, the results on bank lending may be driven by the shock that correlates with CIP deviations rather than arbitraging CIP deviations by banks.

Controlling for time-invariant characteristics of banks as well as their relationships with firms helps mitigate this concern. Because the fixed effects do not capture the time-varying component of banks' characteristics, I also add lagged time-varying bank controls. These controls include soles and dollar deposits scaled by total assets, log of total assets, return over assets, and share of liquid assets in soles and dollars. However, I find that the regressions without lagged bank controls yield very similar results.

The coefficient of interest, α_1, measures the percentage increase in bank lending of increasing arbitrage intensity by 1 (i.e., increasing $\hat{\beta}$ by 1) after a 1-percentage-point increase in the cross-currency basis when lending to the same firm in the same month. Then $\hat{\alpha}_1$ simultaneously compares (a) the lending of the same bank to the same firm at different levels of CIP deviations and (b) the lending to the same firm, in the same month, of arbitrage-intensive banks relative to less-arbitrage-intensive ones.

The main takeaway from estimating the baseline regression is that an increase in the cross-currency basis increases the share of dollar lending relative to soles lending. These results are all significant at 1% significance level. They are also consistent across alternative specifications. Banks that allocate 1-percentage-point more of their assets to arbitraging a 1-percentage-point increase in the cross-currency basis increase their dollar lending by 11 to 40-percentage-points relative to their soles lending. In terms of standard deviations, a one-standard-deviation increase in the cross-currency basis makes banks that respond by arbitraging one-standard-deviation more

[49] I compute these numbers from the dataset that contains all forward transactions of banks, including those trades between MXN and CLP against PEN.

increase dollar lending relative to soles lending by 69-percentage-points, making the share of dollar borrowing increase by 2.43 basis points.

Decomposing this result into soles borrowing and dollar borrowing, I find that this result is driven not only by an increase in dollar lending but also by a decrease in soles lending. The range depends on the sample. I obtain the most conservative result, 11%, when including only firms that were already borrowing in dollars and soles. I get the largest result when including all firms. My benchmark includes all firms. In net terms, my results represent a change in the currency denomination of the loans and a small change in total loans.

Table 3 and Table 4 show the previous results. Table 3 shows the first-stage results for various specifications, including the baseline specification (Column 3). Here, the instrument is statistically significant and stable across specifications. Its strong correlation with USDPEN cross-currency basis also indicates the absence of a weak-instrument problem.

Table 4 shows the second-stage results for the IV baseline specification using five different dependent variables: *log of dollar loans, log of soles loans, log of total loans, the share of dollar loans, and the difference between log of dollar loans and log of soles loans*. The first-stage results for this specification are those in Column 3 of Table 3. These are the results including all firms. The most conservative findings, which result from considering only those borrowing in soles and dollars, appear in row 5 of Table A.VI in the Online Appendix.

The analogous OLS regression for all the columns reported in Table 4 is reported in Online Table A.V. Both types of model, OLS and IV, show the same pattern and statistical significance, but the differences between OLS and IV show a consistent negative bias. The bias is as expected and can be explained as follows. A bank that decides to lend more dollars, to meet regulations, will need to hedge.[50] Unless the bank borrows and lends in the same currency, the bank will need to hedge by selling dollars forward. As a market maker, when the bank sells dollars forward, it will set downward pressure to the forward outright ($F_{t,t+n}$ in Equation (1)) and decrease the cross-currency basis. This ultimately leads to a lower cross-currency basis, higher dollar lending, and lower soles lending (if lending more in dollars means banks prefer to lend less in soles), and hence,

[50]By regulation, banks need to match the currency of their assets with those of their liabilities.

goes against finding a result through the mechanism proposed in this paper. Thus, as expected, OLS estimates are significantly lower than the IV estimates.

The baseline regression specification addresses various concerns, but some concerns might linger, including (a) the correlation between the basis and other macroeconomic shocks, (b) the heterogeneity across banks, (c) the demand effect coming from the relationship between the exchange-rate and foreign trade, (d) the role played by different types of loans, (e) the effect of calculating CIP deviations using different variables and tenors, (f) the effect of calculating CIP deviations at the bank level instead of at the market level, and (g) the effect of alternative arbitrage intensities. I address these concerns in Section 5.4. My results are robust to the various sets of different specifications and mechanisms.

5.4 Robustness

Next, I address several potential concerns that the baseline specification may have left open. The tables for all robustness checks are in the Online Appendix.

The Exchange Rate. One concern is that macroeconomic shocks that correlate with CIP deviations (including changes in the exchange-rate) could themselves explain my results.[51] In this section, I focus on the main known macroeconomic correlation, the one between CIP deviations and exchange-rate (Avdjiev et al., 2019).

Figure 6 shows that soles (PEN) depreciate as the cross-currency basis increases. This positive correlation between the exchange-rate and the cross-currency basis can confound the effects of arbitraging CIP deviations. Through independent channels, a depreciation of the local currency and an increase in the cross-currency basis can both generate an excess supply of dollar funding and a shortage of local currency funding provided to banks. As the sol depreciates, households and firms will prefer to switch their savings from soles to dollars. Through this channel, which I refer to as the exchange-rate channel, as the sol depreciates, banks would increase dollar lending and

[51] Policy changes such as central bank exchange-rate interventions, changes in local reserve requirements, capital controls (which themselves include changes in foreign reserve requirements and forward limits) could be at play here too. For brevity, I leave the analysis of policy changes to Online Appendix B, where I also describe how these policies are common across emerging economies. In sum, I find that policy changes do not affect my results.

decrease soles lending to mirror what is happening to their funding side. Although the net effect on bank lending is uncertain — because households and firms will probably demand more soles borrowing as the sol depreciates — if the bank supply side dominates, it is possible the baseline results are picking up the correlation with the exchange-rate rather than arbitraging CIP deviations.

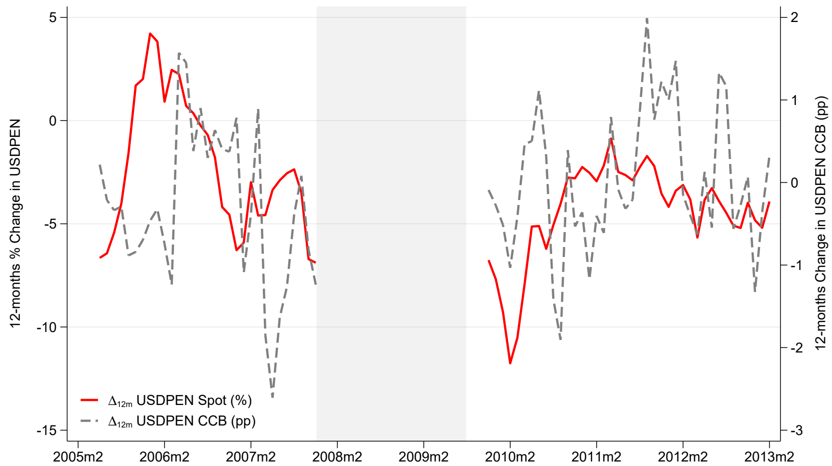

Figure 6: CIP Deviations and Exchange-Rate

This plot shows the yearly changes in USDPEN cross-currency basis against the yearly changes in exchange-rate. The red line corresponds to the changes in the spot, while the gray line corresponds to changes in the cross-currency basis. The cross-currency basis corresponds to the 1-month basis. The shaded gray area represents the Global Financial Crisis. I am not showing these months, in order to prevent an outlier period from affecting the results and because the significant deviations affect the scale.

However, for the exchange-rate channel to threaten the results, it is not enough for it to be correlated with the cross-currency basis. The exchange-rate channel must also be correlated with banks' sensitivities to arbitrage ($\hat{\beta}_b$). Specifically, to invalidate the results, because the estimation relies on comparing bank lending across banks with varying sensitivity to arbitrage, we also need the exchange-rate channel to have a greater effect on those banks with a higher sensitivity to arbitrage.

To check whether banks that arbitrage more are the more affected by the exchange-rate channel, I compute the bank-level sensitivity of bank deposits after changes in the exchange-rate and contrast that result with the bank-level arbitrage intensity. I use the sensitivity to bank deposits because this would be the direct channel through which the exchange-rate affects banks' liquidity. To compute this sensitivity, I estimate the following time-series regression separately for each bank:

$$\left(\frac{\text{Deposits}}{\text{Assets}}\right)_{bt} = \alpha_b^0 + \alpha_b^1 \log(\text{FX})_t + \varepsilon_{bt} \qquad \forall b \in B \tag{11}$$

where the numerator of the dependent variable is either deposits in soles, deposits in dollars, or total deposits. *Log(FX)* is the log of the exchange-rate.

I find that the deposit sensitivity to the exchange-rate does not most strongly affect the banks that arbitrage the most. Table A.VII shows the summary statistics of the estimated coefficients, splitting banks into three groups,[52] depending on their arbitrage intensity.[53] The most arbitrage-intensive banks are those for which dollar deposits increase the least when the sol depreciates. For soles, the least arbitrage-intensive banks show the greatest reduction in sol deposits as the sol depreciates. For this reason, the greater reduction in soles bank lending in banks that arbitrage more after an increase in the cross-currency basis cannot derive from the exchange-rate channel.

If anything, the exchange-rate channel works against finding a result in soles. Similarly, it is unlikely that the results for dollar lending are coming from the exchange-rate channel, because the banks that arbitrage the most are not those with the greatest increase in dollar deposits as the basis increases and the exchange-rate depreciates. I corroborate this in Table A.VIII, which shows that the baseline results are robust to adding the interaction between arbitrage intensity (β) and *log(FX)*.

Bank characteristics. Because shocks that affect banks differently could threaten the results if these shocks are correlated to both the cross-currency basis and the sensitivity to arbitrage, I take a closer look at the possible role that bank characteristics could be playing in the regression. I do not find evidence that suggests that bank characteristics affect the regression results. First, the second row of Table A.VI shows the second-stage results for a sample that includes only the four largest banks. These banks are homogeneous. In this sample, the results get stronger.[54] Second, alternative specifications that exclude all time-varying bank controls — including measures of sol

[52] I use discontinuous ranges $\hat{\beta}$ in Table A.VII to show that there are discontinuous jumps in the accumulation of banks, which allows me to sort banks into the three groups shown in the table.

[53] This sensitivity is very similar if I use lagged exchange-rate changes (in case the deposit response was sluggish) or leading exchange-rate changes (in case the was deposit response was anticipated).

[54] The largest differences regarding Table 4 derive from a larger coefficient on dollar lending, which leads to an increase in total lending.

and dollar deposits, total assets, profitability, and liquidity — yield results that are very similar to the baseline model. Moreover, adding bank fixed effects even strengthens the results. These results, shown in Table A.IX, include dropping bank controls and adding fixed effects one by one. In general, Table A.IX suggests that the results are not only robust to changes in the specification regarding banks, but also to changes in the rest of the variables.

Firms with foreign trade. The correlation between the cross-currency basis and the exchange-rate could affect the results through an alternative channel: the effect that the exchange-rate has on foreign trade. Exporters could face greater demand as the sol depreciates, in which case these firms may increase their credit demand. Given that their revenues are in dollars, it is also possible they demand dollar loans. If banks that arbitrage more specialize in lending to firms that engage in foreign trade, then the results could be driven by demand from net exporters.

To mitigate this problem, I estimate the baseline regression after dropping all exporter and importer firms from the sample.[55] The baseline results are robust to excluding firms with foreign trade. Row 3 of Table A.VI shows the results. I have also done robustness checks dropping firms that hedge with derivatives. The results remain very similar, because very few firms hedge.

Type of loan. Another concern is that credit demand for a particular type of loan could lead some firms to borrow from a specific bank and in a specific currency. To alleviate this concern, I narrow the sample to the most common type of loan: commercial loans.[56] These constitute 50% of loans to firms in Peru. Row 4 of Table A.VI shows that the baseline results are even strengthened by this modification. The coefficients in soles and dollars are larger in absolute terms, while still being statistically significant at 1% significance level. This indicates that the baseline results are not driven by particular demands for specific types of loans or bank specialization in a specific type of loan.

Differing market-based calculations for CIP deviations. Another worry is that the interbank rates I use to compute the market CIP deviations do not reflect the actual cost and investment

[55] I define an exporter/importer as a firm that exports or imports every year. Defining an exporter/importer as a firm that has ever exported/imported yields similar results.

[56] The sample excludes several other types of loans, including foreign trade loans, leasing, real estate, credit cards, and overdrafts.

opportunities of banks. To alleviate this concern, I further verify that the results are not driven by the exchange-rate and interest rates I use to compute CIP deviations. First, Table A.X shows that the results are robust to using CIP deviations that account for bid-ask spreads.[57] Second, some might wonder whether dollar interbank rates are the best ones to use. Table A.X shows that the results are robust to using the Libor and the inferred put-call parity-relationship rates from van Binsberger et al. (2021) (rows 3 and 4). Third, one might worry that interbank rates might not be capturing well the funding costs of banks, so I compute the cross-currency basis using banks' deposit rates[58] (row 5). Table A.X shows that the results hold.[59] Fourth, when I also use alternative cross-currency basis tenors (3 months and 12 months), the results are robust (rows 6 and 7).

The aforementioned market-based calculations (rows 1–7 of Table A.X) use the same security for the funding and investment legs. However, the funding and investment securities could differ. As described in Section 3.1, the most important funding security for soles and dollars are bank deposits. The most important investment securities are the Central Bank of Peru's dollar deposits and soles certificates of deposit (CDs). Hence, a more precise computation of CIP deviations considers the direction of banks' positions and uses the relevant investment and funding rates.

With this in mind, I compute an alternative CIP deviation that considers the banking system's aggregate forward and spot position. This casts light on whether to use sol or dollar rates for funding or investment. When the basis is negative, banks lend soles in the money-market but fund soles synthetically. Since funding soles synthetically means borrowing dollars and hedging the exchange-rate by buying dollars forward and selling in spot, when computing CIP deviations, I take the dollar deposit rate as the funding rate. In contrast, I take the soles short-term CD of the Central Bank as the lending rate. When the basis is positive, on the other hand, banks' positions

[57]The effective cross-currency basis that accounts for bid-ask spreads depends on the sign of the basis. For example, when the cross-currency basis is negative, to implement the arbitrage, a price taker investor needs to (i) borrow U.S. dollars at the ask rate, (ii) sell dollars at the bid spot rate, (iii) invest soles at the bid rate, and (iv) buy dollars forward at the ask forward rate. Therefore, when the cross-currency basis is negative, I compute the basis taking the spot bid price and the forward ask price. When the cross-currency basis is positive, I use the spot ask price and the forward bid price. To account for the bid-ask spread in the money-market, I follow Du, Tepper, and Verdelhan (2018) and use a bid-ask spread of 9 basis points. Therefore, the dollar bid/ask rate is the midmarket rate minus/plus 4.5 basis points.

[58]Because deposits are subject to reserve requirements, I adjust the deposit rates to include the cost of the reserve requirements. That is, the interest rate is $y = \frac{1-req+y^{raw}}{1-req} - 1$, where y^{raw} is the deposit rate without reserve requirement, and *req* is the reserve requirement (in percentage terms).

[59]I cannot compute the CIP deviations using foreign borrowing, because I do not have foreign borrowing rates.

show that they are selling dollars forward and buying in spot. Therefore, I use sol deposit rates as funding rates and dollar deposits at the Central Bank as investment rates. The last row of Table A.X shows the results, confirming that the simpler version of using interbank rates is a good proxy for a more rigorous computation.

Bank-specific CIP deviations. The previous robustness checks use alternative specifications for market-based CIP deviations. These specifications rely on market data on rates and the exchange-rate. I improve over those measures by exploiting the granularity of my data and computing bank-specific CIP deviations. These deviations rely on using the forward trade-level data to obtain the forward premium for each bank.[60] I use the interest rates on new deposits for each bank as funding rates. I adjust these with the reserve requirements on each date. For sol investment rates, I use the rate at which each bank purchased the soles CDs of the Central Bank. For dollar investment rates, I use banks' dollar deposits at the Central Bank. The justification for using these rates comes from analyzing Table A.X (see discussion in Section 3.1). The CIP deviations computed with these rates are are arguably the most precise measure of CIP deviations that we can obtain.

However, the analysis using bank-specific CIP deviations is subject to two important caveats. First, I cannot use an IV approach, because banks in Peru do not trade other currencies frequently. This prevents me from computing bank-specific CIP deviations for currencies besides the USDPEN pair. Because the baseline bank-lending results indicate that the OLS estimates are biased downward, we can take the results based on bank-specific CIP deviations as lower bounds. Second, the analysis should be done only with the largest banks, because smaller banks do not trade every day. Thus, we cannot compare the monthly average[61] of bank-specific CIP deviations across banks.[62] The differences might only be a reflection of the fact that banks trade on different

[60]Banks need to report the initial spot rate at the time the forward contract was closed. I have corroborated the validity of this self-reported variable using market data, and I have conducted interviews with traders in Peru; the self-reported spot variable is very reliable.

[61]I require monthly averages to merge with the credit registry.

[62]The current baseline regression specification is not affected by the problem that some banks do not trade every day. I know that if the bank does not trade forward and does not change its forward position that is offset with its spot position when the cross-currency basis changes, it is not responding to the arbitrage opportunities measured by the market. Because I can accurately measure this variable on both a daily and a monthly basis for all banks, using the arbitrage-intensity, or β_b, is comparable across banks. In fact, it accurately reflects that some banks do not trade every day by having lower betas.

days. Hence, to reduce noise, I will limit the analysis to the four largest banks, but the results are very similar when using all banks.

Under these caveats, I present the OLS estimation of the second stage of the baseline regression (Equation (10b)) for Peru's largest four banks. Since I have computed the basis at the bank level, I also compute a new arbitrage intensity, $\hat{\beta}_b^{CCB_b}$, using the banks' specific CIP deviations, and I use this to interact with the bank-specific basis, CCB_b. Table A.XI shows that the results are robust and of similar magnitude as the OLS estimations with the baseline regression specification. The first line shows the results using the bank-level deviations using investment and deposit rates as described. The second line, for robustness, shows the results when computing CIP deviations using adjusted deposit rates for both funding and investment. This second line shows larger effects than the baseline OLS results of Table 4.

Alternative arbitrage intensities. Another concern is that the baseline specification uses a common estimated $\hat{\beta}$ between OLS and IV estimations. However, the "matched" position of the bank is affected when banks that decide first to lend in dollars and then hedge by selling dollars forward. As the bank sells dollars forward, the basis can decrease, while selling dollars forward also makes the matched position more negative. Because of this, $\hat{\beta}$ could be biased. Therefore, as a robustness check, I estimate $\hat{\beta}$ in Equation (9) but instrumenting the USDPEN basis with that of the average between USDCLP and USDMXN. The results (see the second row of Table A.XII) are robust to the change in the estimation of $\hat{\beta}$.

Similarly, Table A.XII shows that the results are robust to a variety of changes in the regressors, including not using $\hat{\beta}$ to sort banks. This table compares the banks that arbitrage the most with those that either do not arbitrage or arbitrage significantly less (row 3), only using the USDPEN basis (row 4), and using the lagged arbitrage position, Matched/Assets, as the regressor (row 5). This last row shows only the OLS regression, because there is no IV for Matched/Assets. Also, because month fixed effects cannot be added when using only the USDPEN basis as the regressor, row 4 uses only bank-firm fixed effects and lagged bank controls.

Standard errors. I also perform various robustness checks regarding the standard errors and show that the statistical significance of the results holds. This check is important because the banking system in Peru, as in most countries, is composed of a small number of banks. Hence, clustering at the bank level can yield inconsistent standard errors with so few clusters. Because of this, the regressions I report use firm and month clusters. To confirm that the significance of the results is not driven by the choice of clustering, Table A.XIII reports the baseline specification under different clustering options, including at the bank level. In particular, I show that the statistical significance of the results holds when clustering by bank only, by bank and firm, by bank and date, by firm, and by firm and bank.

6 Conclusion

In this paper, I propose a channel through which CIP deviations affect bank lending. I argue that, although the existence of CIP deviations implies that banks cannot fully arbitrage CIP deviations, banks will attempt to arbitrage them when possible. To do so, banks must borrow in a particular currency. When banks cannot easily expand their balance sheets to fund the additional borrowing required to arbitrage CIP deviations, they can draw funds from their lending division and effectively decrease their lending in the currency required to perform the arbitrage. Because the arbitrage involves borrowing in a particular currency to lend in a different one, banks may substitute lending in one currency for another rather than just decreasing the total quantity lent.

I document that CIP deviations can have broader effects than previously thought. They can affect firms' exchange-rate exposure, which is known to have important effects on the real economy after exchange-rate shocks.

This result also has policy implications. As central banks in partially dollarized emerging economies try to mitigate exchange-rate risk, they must understand how different policies can affect the cross-currency basis and how banks could change their lending in response to such arbitrage opportunities. Understanding this is important when analyzing whether policy interventions have the intended effect.

For example, if central banks lean against the wind when the currency is appreciating, this could reduce the expected returns foreign investors have on carry trade investments. This is worsened if there are macroprudential policies tackling such investments. The investments are often done by selling dollars forward. Closing such investments would generate demand for dollars forward and increase the cross-currency basis. Such an increase in the basis could, therefore, trigger the channel described in this paper. Banks would increase their dollar lending and decrease their soles lending. Effectively, they would be increasing the currency exposure of firms, which would be an unintended consequence. Taking into account the interplay of such actions and the cross-currency basis is therefore important for holistic comprehension about whether policy actions, such as exchange-rate interventions, are generating the intended results.

References

Adler, G., K. S. Chang, R. Mano, and Y. Shao (2021). Foreign exchange intervention: A dataset of public data and proxies. *IMF Working Paper, WP/21/47*.

Aguiar, M. (2005). Investment, devaluation, and foreign currency exposure: The case of mexico. *Journal of Development Economics 78*(1), 95–113.

Aizenman, J., H. Ito, and G. K. Pasricha (2022). Central bank swap arrangements in the covid-19 crisis. *Journal of International Money and Finance 122*, 102555.

Akram, Q. F., D. Rime, and L. Sarno (2008). Arbitrage in the foreign exchange market: Turning on the microscope. *Journal of International Economics 76*(2), 237–253.

Aldunante, F., Z. Da, B. Larrain, Sialm, and Clemens (2022). Non-fundamental flows and foreign exchange rates.

Alfaro, L., M. Calani, and L. Varela (June 2021. (Revised July 2022.)). Granular corporate hedging under dominant currency. *NBER Working Paper Series, No. 28910*.

Amado, M. A. (2022). Macroprudential fx regulations: Sacrificing small firms for stability?

Amador, M., J. Bianchi, L. Bocola, and F. Perri (2020). Exchange rate policies at the zero lower bound. *The Review of Economic Studies 87*(4), 1605–1645.

Ashcraft, A. B. and M. Campello (2007). Firm balance sheets and monetary policy transmission. *Journal of Monetary Economics 54*(6), 1515–1528.

Avdjiev, S., W. Du, C. Koch, and H. S. Shin (2019). The dollar, bank leverage, and deviations from covered interest parity. *American Economic Review: Insights 1*(2), 193–208.

Baba, N. and F. Packer (2009). Interpreting deviations from covered interest parity during the financial market turmoil of 2007–08. *Journal of Banking & Finance 33*(11), 1953–1962.

Baba, N., F. Packer, and T. Nagano (2008, mar). The Spillover of Money Market Turbulence to FX Swap and Cross-Currency Swap Markets.

Ben-David, I., A. Palvia, and C. Spatt (2017). Banks' internal capital markets and deposit rates. *Journal of Financial and Quantitative Analysis 52*(5), 1797–1826.

Blanchard, O., G. Adler, and I. de Carvalho Filho (2015). Can foreign exchange intervention stem exchange rate pressures from global capital flow shocks? *Working Paper No. 15/159*.

Borio, C. E., M. Iqbal, R. N. McCauley, P. McGuire, and V. Sushko (2018). The failure of covered interest parity: Fx hedging demand and costly balance sheets. *BIS Working Papers* (590).

Bruno, V. and H. S. Shin (2014, 12). Cross-Border Banking and Global Liquidity. *The Review of Economic Studies 82*(2), 535–564.

Campello, M. (2002). Internal capital markets in financial conglomerates: Evidence from small bank responses to monetary policy. *The Journal of Finance 57*(6), 2773–2805.

Candian, G., P. De Leo, and L. Gemmi (2023). Managing expectations with exchange rate policy.

Canta, M., P. Collazos, and M. Shiva (2007). Límites a las posiciones de cambio como mecanismo de mitigación del riesgo cambiario . *SBS, Revista de Temas Financieros*, 119–136.

Cao, J. and V. Dinger (2022). Financial globalization and bank lending: The limits of domestic monetary policy. *Journal of Financial and Quantitative Analysis 57*(8), 3223–3251.

Carpio, M. A., L. Keller, and A. Tomarchio (2022). The role of family network in first-credit access.

Cavallino, P. (2019, 04). Capital flows and foreign exchange intervention. *American Economic Journal.Macroeconomics 11*(2), 127–170. Copyright - Copyright American Economic Association Apr 2019; Last updated - 2022-11-03; SubjectsTermNotLitGenreText - Switzerland.

Cenedese, G., P. Della Corte, and T. Wang (2021). Currency mispricing and dealer balance sheets. *The Journal of Finance 76*(6), 2763–2803.

Central Bank of Peru, Inflation Report (December 2010). Inflation Report.

Central Bank of Peru, Nota Informativa (2008). Nota Informativa 67-2008.

Cerruti, E. and H. Zhou (2023). Uncovering cip deviations in emerging markets: Distinctions, determinants, and disconnect.

Cerutti, E. M., M. Obstfeld, and H. Zhou (2021). Covered interest parity deviations: Macrofinancial determinants. *Journal of International Economics 130*, 103447. NBER International Seminar on Macroeconomics 2020.

Cetorelli, N. and L. S. Goldberg (2012a). Banking globalization and monetary transmission. *The Journal of Finance 67*(5), 1811–1843.

Cetorelli, N. and L. S. Goldberg (2012b, nov). Liquidity management of u.s. global banks: Internal capital markets in the great recession. *Journal of International Economics 88*(2), 299–311.

Coffey, N., W. B. Hrung, and A. Sarkar (2009, oct). Capital Constraints, Counterparty Risk, and Deviations from Covered Interest Rate Parity. *SSRN Electronic Journal*.

Correa, R., W. Du, and G. Liao (2020). U.s. banks and global liquidity.

Cremers, K. J. M., R. Huang, and Z. Sautner (2011, feb). Internal capital markets and corporate politics in a banking group. *Review of Financial Studies 24*(2), 358–401.

Dalgic, H. (2020). Financial dollarization in emerging markets: An insurance arrangement.

De Leo, P., G. Gopinath, and S. Kalemli-Ozcan (2023). Monetary policy cyclicality in emerging economies.

Dedola, L., G. Georgiadis, J. Grab, and A. Mehl (2021). Does a big bazooka matter? quantitative easing policies and exchange rates. *Journal of Monetary Economics 117*, 489–506.

Du, W., B. Hebert, and A. W. Huber (2022, 08). Are Intermediary Constraints Priced? *The Review of Financial Studies 36*(4), 1464–1507.

Du, W. and J. Schreger (2022, 01). Sovereign Risk, Currency Risk, and Corporate Balance Sheets. *The Review of Financial Studies 35*(10), 4587–4629.

Du, W., A. Tepper, and A. Verdelhan (2018). Deviations from covered interest rate parity. *The Journal of Finance 73*(3), 915–957.

Endresz, M. and P. Harasztosi (2014). Corporate foreign currency borrowing and investment: The case of hungary. *Emerging Markets Review 21*, 265–287.

Fratzscher, M., O. Gloede, L. Menkhoff, L. Sarno, and T. Stohr (2019, January). When is foreign exchange intervention effective? evidence from 33 countries. *American Economic Journal: Macroeconomics 11*(1), 132–56.

Gabaix, X. and R. Koijen (2021). In search of the origins of financial fluctuations: The inelastic markets hypothesis.

Gabaix, X. and M. Maggiori (2015). International liquidity and exchange rate dynamics. *The Quarterly Journal of Economics 130*(3), 1369–1420.

Gilje, E. P., E. Loutskina, and P. E. Strahan (2016). Exporting liquidity: Branch banking and financial integration. *The Journal of Finance 71*(3), 1159–1184.

Gutierrez, B., V. Ivashina, and J. Salomao (2023). Why is dollar debt cheaper? evidence from peru. *Journal of Financial Economics 148*(3), 245–272.

Hardy, B. (2018, November). Foreign currency borrowing, balance sheet shocks and real outcomes. *BIS Working Papers* (758).

Houston, J., C. James, and D. Marcus (1997). Capital market frictions and the role of internal capital markets in banking. *Journal of financial Economics 46*(2), 135–164.

Houston, J. F. and C. James (1998, aug). Do bank internal capital markets promote lending? *Journal of Banking & Finance 22*(6-8), 899–918.

Humala, A. (2019). Corporate earnings sensitivity to fx volatility and currency exposure: evidence from peru. *Working paper series, Central Bank of Peru*.

Ivashina, V., D. S. Scharfstein, and J. C. Stein (2015). Dollar funding and the lending behavior of global banks. *Quarterly Journal of Economics 130*(3), 1241–1281.

Jung, H. (2023). Real consequences of shocks to intermediaries supplying corporate hedging instruments. *Federal Reserve Bank of New York Staff Reports, no. 989*.

Kalemli-Ozcan, S., H. Kamil, and C. Villegas-Sanchez (2016, 10). What Hinders Investment in the Aftermath of Financial Crises: Insolvent Firms or Illiquid Banks? *The Review of Economics and Statistics 98*(4), 756–769.

Keller, L. (2020). Capital Controls and Misallocation in the Market for Risk: Bank Lending Channel.

Kim, Y. J., L. L. Tesar, and J. Zhang (2015). The impact of foreign liabilities on small firms: Firm-level evidence from the korean crisis. *Journal of International Economics 97*(2), 209–230.

Lamont, O. (1997, mar). Cash flow and investment: Evidence from internal capital markets. *The Journal of Finance 52*(1), 83–109.

Levin-Konigsberg, G., H. Stein, V. Garcia Averell, and C. Lopez Castanon (2023). Risk management and derivatives losses. *Federal Reserve Bank of Boston*.

Liao, G. and T. Zhang (2022a). The hedging channel of exchange rate determination.

Liao, G. and T. Zhang (2022b). The hedging channel of exchange rate determination.

Mancini-Griffoli, T. and A. Ranaldo (2011, feb). Limits to Arbitrage During the Crisis: Funding Liquidity Constraints and Covered Interest Parity. *SSRN Electronic Journal*.

Martin, A., E. Moral-Benito, and T. Schmitz (2021, March). The financial transmission of housing booms: Evidence from spain. *American Economic Review 111*(3), 1013–53.

Mohanty, M. and B.-e. Berger (2013). Central bank views on foreign exchange intervention. *BIS Papers N73*.

Montamat, G. (2020). Stubborn dollarization: Love for the dollar and fear of the peso.

Puriya, A. and F. Brauning (2020, 10). Demand Effects in the FX Forward Market: Micro Evidence from Banks' Dollar Hedging. *The Review of Financial Studies 34*(9), 4177–4215.

Rancière, R. G. and A. Tornell (2016). Financial liberalization, debt mismatch, allocative efficiency, and growth. *American Economic Journal: Macroeconomics 8*, 1–44.

Rime, D., A. Schrimpf, and O. Syrstad (2020). Covered interest parity arbitrage. *Available at SSRN 2879904*.

Salomao, J. and L. Varela (2021, 06). Exchange Rate Exposure and Firm Dynamics. *The Review of Economic Studies 89*(1), 481–514.

Sarno, L. and M. P. Taylor (2001, 09). Official intervention in the foreign exchange market: Is it effective and, if so, how does it work? *Journal of Economic Literature 39*(3), 839–868. Copyright - Copyright American Economic Association Sep 2001; Last updated - 2023-07-05; CODEN - JECLB3; SubjectsTermNotLitGenreText - United States–US.

Shin, H.-H. and R. M. Stulz (1998). Are internal capital markets efficient? *The Quarterly Journal of Economics 113*(2), 531–552.

Slutzky, P., M. Villamizar-Villegas, and T. Williams (2020). Drug money and bank lending: The unintended consequences of anti-money laundering policies. *Available at SSRN 3280294*.

Tobal, M. (2018). Currency mismatch in the banking sector in latin america and the caribbean. *International Journal of Central Banking*.

van Binsberger, J. H., W. Diamond, and M. Grotteria (2021). Risk free interest rates. *Journal of Financial Economics*.

Verner, E. and G. Gyöngyösi (2020, sep). Household debt revaluation and the real economy: Evidence from a foreign currency debt crisis. *American Economic Review 110*(9), 2667–2702.

Wallen, J. (2019). Markups to financial intermediation in foreign exchange markets. *Working paper*.

Table 1: Evidence Consistent With Arbitrage of CIP Deviations

This table shows the results of estimating linear regressions of the different accounts used for CIP arbitrage on Peru's cross-currency basis, separated by the months when it was positive and negative. In all columns, the dependent variable is stated at the header. Variables are written as a percentage of total assets (0–100 scale). Regressions in Panel A were estimated using the monthly time series of aggregate accounts of banks' balance sheets. Regressions in Panel B were estimated using data at the bank-month level, with bank fixed effects. Regressions in Panel C were estimated restricting the sample of Panel B to the banks that arbitrage the most. Panel D covers banks that arbitrage the least. All regressions have been estimated over a sample between February 2005 and 2013 (excluding the Global Financial Crisis (GFC)). All USD accounts were transformed into PEN with the constant FX of February 2005. In all panels, HAC standard errors were used, allowing for 3-month autocorrelation. In addition, standard errors in Panels B, C, and D were clustered by month. t-stats are in parentheses. Significance stars follow conventional levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

	Borrowing				**Currency Exchange**		**Lending**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	PEN Liab: Ibk Loans	USD Liab: Ibk Loans	PEN Liab: Fin Obl	USD Liab: Fin Obl	Spot Position	Fwd+Swap Position	PEN Asset: CB + Gvt	USD Asset: CB + Gvt	PEN Asset: Investments	USD Asset: Investments
Panel A: Aggregate Banking System										
OLS: Positive CCB (%)	0.37**	-0.04	1.22***	-2.44***	4.21***	-3.56***	-2.61**	0.03	-1.09	1.34***
	(2.45)	(-1.36)	(2.60)	(-2.98)	(6.99)	(-6.59)	(-2.12)	(0.68)	(-1.00)	(4.31)
OLS: Negative CCB (%)	0.05	-0.07*	-0.29*	-2.98***	2.61***	-2.06***	0.37	0.09**	0.22	0.67***
	(1.01)	(-1.89)	(-1.71)	(-4.52)	(5.50)	(-4.99)	(0.34)	(2.14)	(0.18)	(3.24)
Observations	77	77	77	77	77	77	77	77	77	77
Panel B: Bank-Level Regressions										
OLS: Positive CCB (%)	0.35***	-0.02	0.46	-1.11***	3.48***	-2.48***	-1.76**	0.09*	-0.83	1.02***
	(2.85)	(-0.44)	(1.14)	(-3.25)	(6.01)	(-4.83)	(-2.39)	(1.85)	(-1.19)	(2.93)
OLS: Negative CCB (%)	0.08	-0.08	-0.29**	-0.87***	2.20***	-1.86***	-0.08	0.08***	-0.36	0.48***
	(1.62)	(-1.07)	(-2.16)	(-3.23)	(4.74)	(-4.46)	(-0.08)	(3.00)	(-0.34)	(3.22)
Observations	873	873	873	873	873	873	832	758	873	873
Panel C: High-Arbitrage Banks										
OLS: Positive CCB (%)	0.66***	0.00	1.20***	-2.21***	5.42***	-4.31***	-2.52**	-0.01	-1.22	0.80**
	(3.88)	(0.03)	(2.79)	(-3.34)	(5.83)	(-4.82)	(-2.28)	(-0.20)	(-1.22)	(2.43)
OLS: Negative CCB (%)	0.16*	-0.15	-0.23*	-2.05***	3.74***	-3.36***	-0.22	0.09**	-0.64	0.54***
	(1.93)	(-1.04)	(-1.78)	(-4.36)	(4.86)	(-4.59)	(-0.19)	(2.03)	(-0.45)	(3.22)
Observations	479	479	479	479	479	479	476	454	479	479
Panel D: Low-Arbitrage Banks										
OLS: Positive CCB (%)	-0.04	-0.05**	-0.46	0.27	1.05***	-0.18***	-0.77**	0.22***	-0.35	1.28***
	(-0.45)	(-2.30)	(-1.11)	(0.66)	(5.40)	(-3.06)	(-2.13)	(7.46)	(-0.88)	(3.14)
OLS: Negative CCB (%)	-0.01	-0.00	-0.38	0.55**	0.32**	-0.06	0.12	0.07***	-0.03	0.41**
	(-0.21)	(-0.19)	(-1.60)	(2.05)	(2.11)	(-0.67)	(0.18)	(3.30)	(-0.04)	(2.48)
Observations	394	394	394	394	394	394	356	304	394	394

Table 2: Evidence Consistent With Liquidity Problems Related to CIP Deviations

This table shows the results of estimating linear regressions of different proxies for liquidity constraints on Peru's cross-currency basis, separated by the months when it was positive and negative. In all columns, the dependent variable is stated at the header. The group to which the variable belongs is stated in bold. Variables are written as a percentage of assets (0–100 scale) or as percentage points, if they are interest-rate spreads. Regressions in Panel A were estimated using the monthly time series of aggregate accounts of banks' balance sheets. Regressions in Panel B were estimated using data at the bank-month level and with bank fixed effects. Regressions in Panel C were estimated restricting the sample of Panel B to the banks that arbitrage the most. Panel D covers the subsample corresponding to the banks that arbitrage the least. All regressions have been estimated over a sample between February 2005 and 2013 (excluding the GFC). All USD accounts were transformed into PEN with the constant FX of February 2005. In all panels, HAC standard errors were used, allowing for 3-month autocorrelation. In addition, standard errors in Panel B, C, and D were clustered by month. t-stats are reported in parentheses, and significance stars follow conventional levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	Spreads				**Liquidity Ratios**	
	(1)	(2)	(3)	(4)	(5)	(6)
	PEN Spread: Term Dep.	USD Spread: Term Dep.	PEN Spread: Interbank	USD Spread: Interbank	PEN Liq. (% Assets)	USD Liq. (% Assets)
Panel A: Aggregate Banking System						
OLS: Positive CCB (%)	0.36***	-0.43***	0.04	-0.42**	-3.13***	4.41***
	(4.12)	(-2.85)	(1.30)	(-2.20)	(-2.86)	(6.82)
OLS: Negative CCB (%)	0.25***	-0.56***	0.02**	-0.64***	-2.05***	1.51***
	(3.14)	(-3.97)	(1.99)	(-3.40)	(-3.74)	(3.26)
Observations	77	77	77	77	77	77
Panel B: Bank-Level Regressions						
OLS: Positive CCB (%)	0.40***	-0.82***	0.06	-0.53**	-2.59***	2.66***
	(3.41)	(-4.32)	(1.39)	(-2.28)	(-4.08)	(6.04)
OLS: Negative CCB (%)	0.26**	-0.49***	-0.00	-0.60***	-1.97***	0.55
	(2.30)	(-3.77)	(-0.04)	(-2.78)	(-3.71)	(1.37)
Observations	872	873	778	702	873	873
Panel C: High-Arbitrage Banks						
OLS: Positive CCB (%)	0.41***	-0.68***	0.06	-0.50**	-3.64***	3.57***
	(4.74)	(-4.51)	(1.19)	(-2.31)	(-3.70)	(5.51)
OLS: Negative CCB (%)	0.22**	-0.50***	0.00	-0.62***	-2.96***	0.81
	(2.62)	(-3.76)	(0.12)	(-3.07)	(-3.79)	(1.25)
Observations	478	479	465	458	479	479
Panel D: Low-Arbitrage Banks						
OLS: Positive CCB (%)	0.40**	-0.98***	0.07*	-0.60**	-1.27**	1.53***
	(2.38)	(-3.92)	(1.70)	(-2.19)	(-2.41)	(4.37)
OLS: Negative CCB (%)	0.31*	-0.49***	-0.00	-0.56**	-0.78*	0.24
	(1.99)	(-3.06)	(-0.24)	(-2.14)	(-1.76)	(1.33)
Observations	394	394	313	244	394	394

Table 3: First-Stage Results

This table presents the first-stage results for three alternative specifications. They all show the relationship between the USDPEN cross-currency basis and the average basis of USCLP and USDMXN and have been estimated using alternative specifications of Equation (10a). The dependent variable for all specifications is $CCB_{t-1}^{Peru} \times (\hat{\beta})$. Both the USDPEN and the average of USDCLP and USDMXN are expressed on a 0–100 scale. Column 1 has no bank controls and no bank fixed-effects. Column 2 adds bank controls only. Column 3 includes bank controls and bank fixed effects. Column 3 corresponds to the first stage of the baseline specification (Equation 10a). The F-statistic is that of the first stage, given by Kleibergen-Paap rk Wald F statistic. T-statistics are in parentheses. Standard errors are those from the joint estimation with the second stage, which are clustered by date and firm. ***, **, and * denote significance at 1%, 5%, and 10% respectively. The sample period goes from February 2005 to February 2013, excluding the GFC.

	(1)	(2)	(3)
$\text{CCB}_{t-1}^{\text{Chile,Mex}} * (\hat{\beta})$	0.811***	0.591***	0.576***
	(5.43)	(4.33)	(4.22)
Bank Controls	No	No	Yes
Bank FE	No	Yes	Yes
F	29.45	18.77	17.79
Observations	1348040	1348040	1348040

Table 4: Effect of Arbitraging CIP deviations on Bank Lending: Baseline Specification

This table presents the baseline results of the effect of arbitraging CIP deviations on bank lending. The specification is given by Equation 10b. The five columns show the IV estimates. The dependent variables in logarithm have been multiplied by 100. The ratio of dollar to total loans is expressed on a 0–100 scale. T-statistics are in parentheses. Standard errors are those from the joint estimation with the first stage. These have been are clustered by date and firm. ***, **, and * denote significance at 1%, 5%, and 10% respectively. The sample period goes from February 2005 to February 2013, excluding the GFC. To prevent the results of the dollar loans from reflecting changes in the exchange rate, the dollar loans have been converted to soles using a constant exchange rate (corresponding to February 2005)

	IV				
	Log(PEN)	Log(USD)	Log(Total)	Ratio	Log(USD)-Log(PEN)
$\text{CCB}_{t-1}^{\text{Peru}} * (\hat{\beta})$	-24.30***	16.29***	3.377**	1.422***	40.58***
	(-3.44)	(3.50)	(2.18)	(3.40)	(3.74)
Firm * Month FE	Yes	Yes	Yes	Yes	Yes
Bank * Firm FE	Yes	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes	Yes
Firm Cluster	18,374	18,374	18,374	18,374	18,374
Month Cluster	77	77	77	77	77
Observations	1,348,040	1,348,040	1,348,040	1,348,040	1,348,040

ONLINE APPENDIX

Table A.I: Summary Statistics: Banking System's Assets and Liabilities, by Currency and Tenor (%)

This tables shows summary statistics for the banking system's assets and liabilities, by currency and tenor (%). The sample period goes from February 2005 to February 2013, excluding the GFC.

	PEN Assets (%)									USD Assets (%)								
	1 Month or Less			6 Months or Less			1 Year or Less			1 month or less			6 Months or Less			1 Year or Less		
	Mean	SD	N	Mean	SD	N	Mean	SD	N	Mean	SD	N	Mean	SD	N	Mean	SD	N
Active Credits	40.36	14.14	77	51.96	6.89	77	52.79	6.69	77	36.11	9.97	77	56.13	7.25	77	56.98	5.51	77
Available	29.57	20.09	77	16.10	12.66	77	13.48	11.03	77	59.34	10.66	77	38.62	7.61	77	37.55	4.42	77
Deposits in BCR	6.28	6.43	77	3.17	3.71	77	2.58	3.16	77	27.24	13.58	77	15.43	7.71	77	12.62	6.16	77
Other Available	23.29	14.40	77	12.92	9.23	77	10.90	8.10	77	32.10	18.95	77	23.19	10.96	77	24.93	5.57	77
Interbank Loans	3.45	2.14	77	1.49	0.89	77	1.16	0.66	77	0.82	1.32	77	0.50	0.91	77	0.42	0.80	77
Investments	20.60	14.40	77	26.23	10.76	77	27.50	11.08	77	1.31	1.27	77	2.61	1.86	77	2.76	1.85	77
PEN CDBCRP	5.78	8.62	77	12.91	10.59	77	22.27	8.38	77	-	-	-	-	-	-	-	-	-
PEN Peruvian Government's Bonds	0.07	0.15	77	0.37	0.57	77	0.85	0.89	77	-	-	-	-	-	-	-	-	-
With Changes in P&L	0.38	1.79	77	0.75	3.28	77	1.15	4.96	77	0.07	0.35	77	0.17	0.76	77	0.15	0.67	77
Other Investments	14.38	11.02	77	12.19	9.92	77	3.23	9.19	77	1.24	1.39	77	2.43	2.23	77	2.60	2.17	77
Other	3.29	1.84	77	2.28	0.96	77	3.18	1.34	77	0.73	1.00	77	0.51	0.64	77	0.57	0.61	77
Other Credit	0.80	0.57	77	0.72	0.35	77	0.78	0.31	77	1.24	1.39	77	1.12	1.19	77	1.14	1.16	77
Receivables	1.93	1.48	77	1.22	0.70	77	1.11	0.58	77	0.45	0.44	77	0.51	0.49	77	0.59	0.50	77
	PEN Liabilities (%)									USD Liabilities (%)								
	1 Month or Less			6 Months or Less			1 Year or Less			1 Month or Less			6 Months or Less			1 Year or Less		
	Mean	SD	N	Mean	SD	N	Mean	SD	N	Mean	SD	N	Mean	SD	N	Mean	SD	N
Liabilities With Public	80.96	7.31	77	84.09	5.09	77	84.92	4.65	77	73.96	6.54	77	73.67	7.98	77	73.99	6.04	77
Demand Deposits	21.72	3.22	77	16.64	2.07	77	17.37	2.28	77	19.89	3.35	77	15.80	3.26	77	16.97	3.39	77
Savings	10.71	2.40	77	15.48	4.43	77	17.86	1.32	77	9.31	3.86	77	12.76	5.44	77	14.80	1.19	77
Term Deposits	45.74	6.07	77	49.47	6.01	77	47.25	4.31	77	41.86	3.93	77	42.45	4.29	77	39.76	5.47	77
Other With Public	2.80	1.73	77	2.49	1.09	77	2.45	0.99	77	2.89	2.10	77	2.66	1.28	77	2.46	1.19	77
Interbank Loans	2.63	1.92	77	1.60	1.17	77	1.39	1.06	77	0.72	0.77	77	0.40	0.44	77	0.33	0.36	77
Financial System Deposits	3.63	0.99	77	3.16	0.71	77	2.81	0.68	77	2.79	1.20	77	3.37	1.43	77	3.65	1.98	77
Adeudados and Other Fin. Obligations	2.99	7.10	77	2.53	4.46	77	2.54	3.92	77	8.45	4.82	77	13.80	7.89	77	13.20	6.75	77
Accounts Payable	2.40	1.01	77	2.17	1.02	77	2.14	1.01	77	0.79	0.39	77	0.59	0.23	77	0.63	0.25	77
Traded Securities	0.38	0.72	77	0.55	0.49	77	0.88	0.49	77	0.16	0.18	77	0.41	0.27	77	0.65	0.23	77
Other	7.01	4.28	77	5.89	2.95	77	5.32	2.20	77	13.13	4.95	77	7.75	3.37	77	7.55	2.94	77

Table A.II: Summary Statistics of CIP Deviations and FX Changes

This table shows descriptive statistics of the monthly time series of the 1-month cross-currency basis (CCB) for three groups of currencies between February 2005 and February 2013, excluding the GFC. The descriptive statistics for the USDPEN currency pair are under "Peru." The cross-currency basis has been computed using mid-closing prices reported in Bloomberg (for FX) and mid-closing prices of interbank rates in dollar and soles taken from the Central Bank of Peru. The descriptive statistics of the average CCB of four Latin American currency pairs: Brazilian real-dollar (USDBRL), Chilean peso-dollar (USDCLP), Colombian peso-dollar (USDCOP), and Mexican peso-dollar (USDMXN) are under "Av.Latam," while "Av.Chile, Mexico" contains those pertaining to the average cross-currency basis of USDCLP and USDMXN. I show this last group because it has greatest correlation with USDPEN. Within each group, the CCB (in row 1) is expressed in percentages (0–100 scale). Rows 2 and 3 describe the summary statistics narrowing the sample to periods when the basis was either positive or negative. Row 4 shows the absolute value of the CCB. Row 5 shows the 1-month change in CCB in percentage points. This has not been annualized. Row 6 is similar, but uses the absolute value of CCB. Row 7 shows the year-over-year changes in the FX of that currency pair. The CCB rows in Av.Latam and Av.Chile and Mexico show the correlation between the CCB of Latam and Chile/Mexico, respectively, with the CCB of Peru. The FX row shows the correlation between the 1-year FX changes and the 1-year changes CCB of the corresponding countries. The last column of this table shows correlations.

	Mean	SD	Min	Max	N	ρ
Peru						
CCB (%)	-0.28	0.74	-2.12	1.98	77.00	
CCB >0 (%)	0.54	0.51	0.08	1.98	24.00	
CCB <0 (%)	-0.65	0.49	-2.12	-0.01	53.00	
$\|CCB\|$ (%)	0.62	0.50	0.01	2.12	77.00	
Δ_1m CCB (pp)	-0.04	0.68	-1.30	2.47	75.00	
$\Delta\_1m\|CCB\|$ (pp)	0.51	0.45	0.01	2.47	75.00	
Δ_12mFX (%)	-3.53	3.02	-11.76	4.22	77.00	0.26
Av.Latam						
CCB (%)	-0.21	0.68	-1.90	1.41	77.00	0.44
CCB >0 (%)	0.48	0.44	0.00	1.41	28.00	
CCB <0 (%)	-0.61	0.42	-1.90	-0.00	49.00	
$\|CCB\|$ (%)	0.56	0.43	0.00	1.90	77.00	
Δ_1m CCB (pp)	-0.01	0.39	-1.45	1.22	75.00	
$\Delta\_1m\|CCB\|$ (pp)	0.28	0.27	0.00	1.45	75.00	
Δ_12mFX (%)	-5.95	6.72	-20.60	8.61	77.00	0.34
Av.Chile, Mexico						
CCB (%)	-0.03	0.55	-1.47	0.88	77.00	0.54
CCB >0 (%)	0.40	0.20	0.03	0.88	43.00	
CCB <0 (%)	-0.57	0.34	-1.47	-0.01	34.00	
$\|CCB\|$ (%)	0.47	0.28	0.01	1.47	77.00	
Δ_1m CCB (pp)	0.00	0.28	-0.63	0.71	75.00	
$\Delta\_1m\|CCB\|$ (pp)	0.22	0.17	0.01	0.71	75.00	
Δ_12mFX (%)	-4.81	6.77	-22.00	9.07	77.00	0.30

Table A.III: Bank-Level, Firm-Level, and Bank-Firm-Level Summary Statistics

This table shows the summary statistics aggregated at the bank level, the firm level and the bank-firm level. $\hat{\beta}$ is the bank-level coefficient estimated from Equation 9, Section 5.1. "Net Matched Position" refers to the forward and swap position of a bank that is matched with the reverse transaction in its spot position.

	Mean	Median	SD	P5	P95	N
Panel A. Bank-Level Data: Balance Sheet, Liquidity, Profitability, and FX						
Balance Sheet						
Assets (Billion USD)	4.22	1.43	6.17	0.23	18.72	873
USD Deposits / Assets (%)	33.11	34.34	14.92	5.24	53.86	873
PEN Deposits / Assets (%)	35.71	32.92	12.50	18.76	61.14	873
USD Credit/ Assets (%)	28.12	31.22	13.31	2.45	49.48	873
PEN Credit/ Assets (%)	34.23	26.73	19.19	12.10	72.09	873
Liquidity and Profitability						
Liquid Assets/ Total Assets (%)	27.02	25.74	10.03	13.62	48.59	873
PEN Liquid Assets / Total Assets (%)	12.64	11.34	6.69	4.53	27.19	873
USD Liquid Assets / Total Assets (%)	14.38	14.95	6.97	2.70	25.61	873
ROA	1.03	1.04	0.97	-0.07	2.74	873
FX Derivatives and $\hat{\beta}$						
$\hat{\beta}^{CIP}$	1.83	1.77	1.90	-0.00	4.96	13
FX Derivatives/ Assets (%)	19.37	9.56	29.95	0.00	83.46	873
Net Matched Position (Million USD)	-6.09	0.00	139.70	-220.20	221.63	873
|Net Matched Position| (Million USD)	74.21	12.24	118.49	0.00	324.23	873
Net Matched Position/ Assets (%)	-0.93	0.00	4.72	-10.35	4.80	873
|Net Matched Position|/ Assets (%)	2.37	0.46	4.18	0.00	11.69	873
Panel B. Firm-Level Data: Share of Firms by Size and Industry						
Share of Firms By Firm Size						
Share of Large Firms (%)	3.0	2.3	1.3	1.6	5.1	77
Share of Medium Firms (%)	18.4	14.8	6.6	10.2	28.2	77
Share of Small Firms (%)	78.6	83.0	7.8	66.6	88.2	77
Share of Credit By Firm Size						
Share of Credit to Large Firms (%)	42.2	42.9	4.5	33.0	48.2	77
Share of Credit to Medium Firms (%)	31.8	32.8	2.0	28.1	34.1	77
Share of Credit to Small Firms (%)	26.1	24.7	3.1	23.2	33.4	77
Credit By Firm						
PEN Credit (Th. USD, Cons FX)	368.11	10.35	3,315.55	0.00	847.28	780,359
USD Credit (Th. USD, Cons FX)	1,101.76	134.18	7,140.37	0.00	3,483.38	780,359
Total Credit (Th. USD, Cons FX)	1,469.87	205.68	8,224.86	4.58	4,839.59	780,359
Number of Bank Relationships	2.14	2.00	1.27	1.00	5.00	780,359
Panel C. Firm-Bank Level Data						
Credit By Firm per Bank						
PEN Credit (Th. USD, Cons FX)	172.36	0.73	1,625.67	0.00	414.87	1,666,605
USD Credit (Th. USD, Cons FX)	515.88	51.97	3,539.25	0.00	1,717.08	1,666,605
Total Credit (Th. USD, Cons FX)	688.24	99.94	3,976.77	1.03	2,367.14	1,666,605

Table A.IV: Evidence Consistent With Foreign Investors Being on the Other Side of the Arbitrage

To determine who is on the opposite side of the arbitrage trade, I look at the correlation between Peru's cross-currency basis and the share of trades linked to local banks purchasing dollars forward, after splitting local banks' counterparties by residency. I use a dataset that includes all of the forward trades executed by local banks. I split the forward trades by residency of the counterparty: (a) foreign investors (nonresidents; "NR" in the table) and (b) local investors (residents; "R" in the table). I aggregate all trades on a daily frequency and compute the daily share of trades that local banks used to buy USD forward. With this, I estimate the following regression for each counterparty group:

$$y_t = \beta_0 + \beta_1 \mathrm{CCB}_t + \varepsilon_t$$

where y_t is either the fraction of trades where the local bank buys dollars forward (columns 1 and 3) or the notional fraction of dollars local banks buy (columns 2 and 4). Columns 1 and 2 show the results for trades done with residents, and columns 3 and 4 show the results for trades done with nonresidents. The regression is on a daily frequency, between February 2005 and February 2013, excluding the GFC.

	(1)	(2)	(3)	(4)
	%NumberTrades	%NotionalTrades	%NumberTrades	%NotionalTrades
Peru CCB (%)	-2.525***	-2.338***	-0.833*	-0.618
	(-4.81)	(-4.40)	(-2.37)	(-1.80)
Observations	1439	1439	1503	1503
Residency	NR	NR	R	R
Adjusted R2	0.0184	0.0137	0.00397	0.00212

t statistics in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.V: Effect of Arbitraging CIP Deviations on Bank Lending: OLS Estimates

This table presents the OLS baseline results of the effect of arbitraging CIP deviations on bank lending. The specification is given by Equation 10b, without instrumenting the USDPEN basis. The dependent variables in logarithm have been multiplied by 100. The ratio of dollar loans to total loans is expressed on a 0–100 scale. T-statistics are in parentheses. Standard errors are from the joint estimation with the first stage and are clustered by date and firm. ***, **, and * denote significance at 1%, 5%, and 10%, respectively. The sample period is from February 2005 to February 2013, excluding the GFC. To prevent the results of the dollar loans from reflecting changes in the exchange rate, I've converted these loans to soles using a constant exchange rate (corresponding to February 2005)

	OLS				
	Log(PEN)	Log(USD)	Log(Total)	Ratio	Log(USD)-Log(PEN)
$\text{CCB}_{t-1}^{\text{Peru}} * (\hat{\beta})$	-6.693***	3.430***	0.409	0.361***	10.12***
	(-3.48)	(3.05)	(0.89)	(3.35)	(3.82)
Firm * Month FE	Yes	Yes	Yes	Yes	Yes
Bank * Firm FE	Yes	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes	Yes
Firm Cluster	18,374	18,374	18,374	18,374	18,374
Month Cluster	77	77	77	77	77
Observations	1,348,040	1,348,040	1,348,040	1,348,040	1,348,040

Table A.VI: Effect of Arbitraging CIP Deviations on Bank Lending: Alternative Samples

This table shows robustness checks under different samples. All specifications, unless noted otherwise, use the same fixed effects (firm-month and bank-month) and lagged bank controls as those used in the baseline specification. The dependent variables in logarithm have been multiplied by 100. The ratio of dollar loans to total loans is expressed on a 0–100 scale. The first five columns show the second-stage IV coefficients of the baseline specification (i.e., with lagged bank controls, bank-firm fixed effects, and month-firm fixed effects) under different samples. The last three columns show other statistics (number of observations, number of firm clusters, and number of month clusters). Row 1 shows the baseline second-stage regression shown in Table 4. Row 2 restricts the sample to Peru's largest four banks. Row 3 restricts the sample to those firms without foreign trade. Row 4 restricts the sample to commercial loans only. (To do this, I started with the loan-level dataset instead of the dataset that aggregated loans at the bank-firm-month level.) Row 5 shows the most conservative sample, limiting the analysis to only those firms borrowing in dollars and soles. Row 6 shows the coefficients for the entire financial system, adding the other financial institutions, including financials and *cajas*. These firms are subject to different banking regulations. Row 7 extends the sample out to February 2018 (the last date for which I have data). T-statistics are in parentheses. I use the dataset aggregated at the bank-firm-month level, except in row 4, where I use the dataset at the bank-firm-loan-month level.

	Estimates					*Other Stats*		
	Log(PEN)	Log(USD)	Log(Total)	Ratio	Log(USD)-Log(PEN)	Obs	Firm Cl.	Month Cl.
(1) Baseline	-24.30***	16.29***	3.38**	1.42***	40.58***	1,348,040.00	18,374.00	77.00
	(-3.44)	(3.50)	(2.18)	(3.40)	(3.74)			
(2) Largest Banks Only	-36.62***	40.93***	8.53***	3.23***	77.55***	1,056,886.00	16,849.00	77.00
	(-3.27)	(4.15)	(2.99)	(3.84)	(3.92)			
(3) Without Foreign Trade Firms	-19.37***	15.16***	0.68	1.35***	34.53***	865,066.00	14,820.00	77.00
	(-3.02)	(2.81)	(0.39)	(2.88)	(3.24)			
(4) Commercial Loans Only	-22.99***	19.66**	1.18	1.77***	42.64***	459,178.00	10,407.00	74.00
	(-2.68)	(2.63)	(0.79)	(2.87)	(2.87)			
(5) Borrowing USD and PEN	-6.02*	5.21*	0.50	0.89**	11.23**	280,282.00	6,189.00	77.00
	(-1.83)	(1.82)	(0.32)	(2.02)	(2.41)			
(6) All Financial Institutions	-17.48***	11.55***	3.80**	0.97***	29.03***	1,438,071.00	19,054.00	77.00
	(-3.01)	(3.14)	(2.52)	(2.92)	(3.40)			
(7) Extended Sample	-16.68**	23.36**	7.32**	2.01**	40.04**	3,652,482.00	34,036.00	137.00
Feb2005-Feb2018	(-2.00)	(2.22)	(2.17)	(2.55)	(2.33)			

Table A.VII: Sensitivity of FX and Arbitrage Intensity

This table shows the summary statistics of the sensitivity of bank deposits to a 1% depreciation, by arbitrage intensity. The arbitrage intensity is measured by β and estimated using Equation 9. The sensitivity of bank deposits to changes in FX is estimated using Equation 11.

	Low $\hat{\beta}$ $0 \leq \hat{\beta} < 0.2$		Medium $\hat{\beta}$ $1.6 \leq \hat{\beta} < 2.6$		High $\hat{\beta}$ $3.5 < \hat{\beta}$	
	Mean	Sd	Mean	Sd	Mean	Sd
$\hat{\beta}$	0.08	0.08	2.11	0.39	4.24	0.59
Δ PEN Dep/Assets to 1% deprec. (pp)	-1.01	0.45	-0.33	0.21	-0.89	0.50
Δ USD Dep/Assets to 1% deprec. (pp)	0.53	0.24	0.83	0.05	0.62	0.76
Δ Total Dep/Assets to 1% deprec. (pp)	-0.47	0.56	0.49	0.16	-0.27	1.04

Table A.VIII: Baseline Results After Controlling for FX

This table shows the results of the regression that modifies the baseline regression to add the interaction between log(FX) and arbitrage intensity ($\hat{\beta}$). All specifications, unless noted otherwise, use the same fixed effects (firm-month and bank-month) and lagged bank controls as those used in the baseline specification. Row 1 shows the baseline coefficients. The dependent variables in logarithm have been multiplied by 100. The ratio of dollar loans to total loans is expressed on a 0–100 scale. T-statistics are in parentheses. Standard errors are from the joint estimation with the first stage and are clustered by date and firm. ***, **, and * denote significance at 1%, 5%, and 10%, respectively. The sample period is from February 2005 to February 2013, excluding the GFC. To prevent the results of the dollar loans from reflecting changes in the exchange rate, I have converted these loans to soles using a constant exchange rate (corresponding to February 2005).

	Log(PEN)	Log(USD)	Log(Total)	Ratio	Log(USD)-Log(PEN)
$\text{CCB}_{t-1}^{\text{Peru}} * (\hat{\beta})$	-17.03***	15.79***	5.220***	1.079***	32.82***
	(-2.88)	(3.28)	(3.06)	(2.97)	(3.32)
$\log(\text{FX})_{t-1} * (\hat{\beta})$	-1.855***	0.356	-0.155	0.0914***	2.211***
	(-4.96)	(1.17)	(-1.37)	(4.03)	(3.67)
Firm * Date FE	Yes	Yes	Yes	Yes	Yes
Bank * Firm FE	Yes	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes	Yes
Firm Cluster	17,070	17,070	17,070	17,070	17,070
Month Cluster	75	75	75	75	75
Observations	1,226,457	1,226,457	1,226,457	1,226,457	1,226,457

Table A.IX: Effect of Arbitraging CIP Deviations on Bank Lending: Alternative Specifications

This table shows robustness checks under different specifications. The first five columns show the second-stage IV coefficients under different specifications. The last three columns show other statistics (number of observations, number of firm clusters, and number of month clusters). Row 1 displays the baseline second-stage regression shown in Table 4. The baseline regression has bank-firm and firm-month fixed effects, as well as 1-month lagged bank controls. The following rows either drop the bank controls and change the fixed effects specifications. Row 2 has no controls but has bank-firm and firm-month fixed effects. Row 3 has no controls and no fixed effects. Row 4 has no bank controls and only bank fixed effects. Row 5 has no bank controls and only firm and bank fixed effects. Row 6 has no controls and firm, bank, and month fixed effects.
The dependent variables in logarithm have been multiplied by 100. The ratio of dollar loans to total loans is expressed on a 0–100 scale. T-statistics are in parentheses. Standard errors are from the joint estimation with the first stage and are clustered by date and firm. ***, **, and * denote significance at 1%, 5%, and 10%, respectively. The sample period is from February 2005 to February 2013, excluding the GFC. To prevent the results of the dollar loans from reflecting changes in the exchange rate, I have converted these loans to soles using a constant exchange rate (corresponding to February 2005).

	Estimates					*Other Stats*		
	Log(PEN)	Log(USD)	Log(Total)	Ratio	Log(USD)-Log(PEN)	Obs	Firm Cl.	Month Cl.
(1) Baseline	-24.30***	16.29***	3.38**	1.42***	40.58***	1,348,040.00	18,374.00	77.00
	(-3.44)	(3.50)	(2.18)	(3.40)	(3.74)			
(2) Benchmark w/o Controls	-25.10***	11.71***	1.00	1.25***	36.81***	1,348,040.00	18,374.00	77.00
	(-3.59)	(3.12)	(0.78)	(3.34)	(3.73)			
(3) No Controls, No FE	-31.64***	22.37**	-3.10	2.51***	54.01***	1,348,040.00	18,374.00	77.00
	(-3.68)	(2.53)	(-1.47)	(3.30)	(3.25)			
(4) No Controls, Bank FE	-32.28***	32.40***	2.00	2.97***	64.68***	1,348,040.00	18,374.00	77.00
	(-3.33)	(3.44)	(1.53)	(3.47)	(3.41)			
(5) No Controls, Firm FE, Bank FE	-30.56***	8.63***	-6.58**	1.80***	39.19***	1,348,040.00	18,374.00	77.00
	(-4.23)	(2.67)	(-2.48)	(4.77)	(4.70)			
(6) No Controls, Firm FE, Bank FE, Month FE	-24.43***	8.98***	1.58	1.04***	33.42***	1,348,040.00	18,374.00	77.00
	(-3.99)	(2.68)	(1.28)	(3.38)	(4.00)			

Table A.X: Effect of Arbitraging CIP Deviations on Bank Lending: Alternative Computations of CIP Deviations

This table shows the second-stage results for the baseline regression when computing the alternative versions of the cross-currency basis. All specifications, unless noted otherwise, use the same fixed effects (firm-month and bank-month) and lagged bank controls as those used in the baseline specification. Row 1 shows the baseline coefficients. Row 2 shows the coefficients when computing CIP deviations using bid-ask spreads for all of these prices, for both the USDPEN basis and the USDCLP and USDMXN basis used as IV. Row 3 computes the cross-currency basis using dollar Libor rates instead of the dollar interbank rate. Row 4 computes the cross-currency basis using the inferred put-call parity relationship rates from van Binsberger, Diamond, and Grotteria (2021). Row 5 computes the cross-currency basis using 1-month term deposit rates, adjusted by reserve requirements. Rows 6 and 7 compute the basis using 3-month and 12-month forward rates, respectively. Row 8 computes the basis using 1-month term deposit rates, adjusted by reserve requirements, as funding rates in USD and PEN, short-term Central Bank soles CD rates for PEN investment rates, and overnight dollar deposit at the Central Bank rates for USD investment rates. The dependent variables in logarithm have been multiplied by 100. The ratio of dollar loans to total loans is expressed on a 0–100 scale. T-statistics are in in parentheses. Standard errors are from the joint estimation with the first stage and are clustered by date and firm. ***, **, and * denote significance at 1%, 5%, and 10%, respectively. The sample period is from February 2005 to February 2013, excluding the GFC. To prevent the results of the dollar loans from reflecting changes in the exchange rate, I have converted these loans to soles using a constant exchange rate (corresponding to February 2005).

	Estimates					*Other Stats*		
	Log(PEN)	Log(USD)	Log(Total)	Ratio	Log(USD)-Log(PEN)	Obs	Firm Cl.	Month Cl.
(1) Baseline	-24.30***	16.29***	3.38**	1.42***	40.58***	1,348,040.00	18,374.00	77.00
	(-3.44)	(3.50)	(2.18)	(3.40)	(3.74)			
(2) CCB With Bid-Ask Spreads	-31.74**	27.27**	7.02	1.92**	59.01**	1,348,040.00	18,374.00	77.00
	(-2.09)	(2.00)	(1.61)	(2.05)	(2.12)			
(3) CCB Using Libor Rates	-46.83*	34.43**	8.38*	2.85*	81.26**	1,348,040.00	18,374.00	77.00
	(-1.98)	(1.99)	(1.81)	(1.95)	(2.03)			
(4) CCB Using vBDG	-43.95**	33.12**	8.41*	2.68**	77.08**	1,348,040.00	18,374.00	77.00
	(-2.03)	(2.06)	(1.86)	(2.00)	(2.09)			
(5) CCB Using Deposit Rates	-24.71***	16.60***	3.11**	1.49***	41.32***	1,348,040.00	18,374.00	77.00
	(-3.09)	(3.20)	(2.00)	(3.09)	(3.32)			
(6) CCB With 3M Rates	-26.68***	20.56***	4.16**	1.71***	47.24***	1,193,597.00	18,204.00	71.00
	(-3.68)	(3.71)	(2.48)	(3.67)	(3.93)			
(7) CCB With 12M Rates	-20.74***	11.47***	1.01	1.14***	32.21***	1,348,040.00	18,374.00	77.00
	(-3.85)	(3.55)	(0.89)	(3.80)	(4.09)			
(8) CCB Using Investment and Funding Rates	-22.07**	26.59***	6.28***	1.99***	48.66***	1,059,198.00	16,881.00	77.00
	(-2.62)	(3.11)	(2.74)	(2.95)	(2.99)			

Table A.XI: Effect of Arbitraging CIP Deviations on Bank Lending: Bank-Level CIP Deviations and Bank-Level Betas

This table shows bank lending OLS regressions using the bank-level cross-currency basis and bank-level betas. All specifications, unless noted otherwise, use the same fixed effects (firm-month and bank-month) and lagged bank controls as those used in the baseline specification. Row 1 shows OLS coefficients using bank-level betas and the cross-currency basis computed with investment and deposit rates. Row 2 shows OLS coefficients using bank-level betas and the cross-currency basis computed with deposit rates. The dependent variables in logarithm have been multiplied by 100. The ratio of dollar loans to total loans is expressed on a 0–100 scale. T-statistics are in in parentheses. Standard errors are clustered by date and firm. ***, **, and * denote significance at 1%, 5%, and 10%, respectively. The sample period is from February 2005 to February 2013, exluding the GFC. To prevent the results of the dollar loans from reflecting changes in the exchange rate, I have converted these loans to soles using a constant exchange rate (corresponding to February 2005).

	Estimates					*Other Stats*		
	Log(PEN)	Log(USD)	Log(Total)	Ratio	Log(USD)-Log(PEN)	Obs	Firm Cl.	Month Cl.
(1) $\text{CCB}^{Inv}_{b,t-1} * \hat{\beta}^{Inv}_{b}$	-5.93***	4.48***	0.79*	0.44***	10.41***	1,059,198.00	16,881.00	77.00
	(-4.03)	(4.03)	(1.77)	(4.72)	(4.66)			
(2) $\text{CCB}^{Dep}_{b,t-1} * \hat{\beta}^{Dep}_{b}$	-8.20***	5.81***	0.95**	0.56***	14.01***	1,057,668.00	16,861.00	77.00
	(-3.97)	(4.39)	(2.06)	(4.54)	(4.59)			

Table A.XII: Effect of Arbitraging CIP Deviations on Bank Lending: Arbitrage Main Regressors

This table shows the second-stage results for the baseline regression when using alternative main regressors. All specifications, unless noted otherwise, use the same fixed effects (firm-month and bank-month) and lagged bank controls as those used in the baseline specification.The dependent variables in logarithm have been multiplied by 100. The ratio of dollar loans to total loans is expressed on a 0–100 scale.
Row 1 shows the baseline coefficients and the baseline regression. Row 2 replaces $\hat{\beta}$ estimated by Equation (8) with one where the USDPEN basis is instrumented by the average basis of USDMXN and USDCLP. I use the superscript "IV" to distinguish this beta from the baseline one. Row 3 replaces $\hat{\beta}$ in the baseline regression with a dummy that takes the value of 1 for banks that arbitrage the most, those with $\hat{\beta} > 3.5$. I chose this threshold because there is a significant gap between this set of banks and the next set of banks, which have a $\hat{\beta}$ of less than 2.6. Row 4 does not use any measure to compare arbitrage intensities across banks; it uses just the USDPEN basis as regressor. Because the baseline regression has Firm×Month fixed effects and I cannot use month fixed effects with this specification, the fixed effects for this model use just firm-bank fixed effects. Row 5 uses only the 1-month lag of negative of "Matched/Assets" as the regressor.
T-statistics are in in parentheses. Standard errors are from the joint estimation with the first stage and are clustered by date and firm. ***, **, and * denote significance at 1%, 5%, and 10%, respectively. The sample period is from February 2005 to February 2013, excluding the GFC. To prevent the results of the dollar loans from reflecting changes in the exchange rate, I have converted these loans to soles using a constant exchange rate (corresponding to February 2005).

Main Regressor	*Estimates*					*Other Stats*		
	Log(PEN)	Log(USD)	Log(Total)	Ratio	Log(USD)-Log(PEN)	Obs	Firm Cl.	Month Cl.
(1) IV: $\text{CCB}_{t-1}^{\text{Peru}} * (\hat{\beta})$	-24.30***	16.29***	3.38**	1.42***	40.58***	1,348,040.00	18,374.00	77.00
	(-3.44)	(3.50)	(2.18)	(3.40)	(3.74)			
(2) IV: $\text{CCB}_{t-1}^{\text{Peru}} * (\hat{\beta}^{IV})$	-24.22***	20.63***	3.40*	1.81***	44.85***	1,348,040.00	18,374.00	77.00
	(-3.24)	(3.62)	(1.98)	(3.58)	(3.67)			
(3) IV: $\text{CCB}_{t-1}^{\text{Peru}} * \mathbf{1}(\text{High Arb Bank})$	-41.81***	40.79***	9.37**	3.39***	82.60***	1,348,040.00	18,374.00	77.00
	(-3.23)	(3.50)	(2.45)	(3.52)	(3.64)			
(4) IV: $\text{CCB}_{t-1}^{\text{Peru}}$	-30.02***	27.28***	-3.25	3.10***	57.30***	1,348,040.00	18,374.00	77.00
	(-3.57)	(3.43)	(-0.96)	(3.97)	(3.85)			
(5) OLS: - $\text{Matched/Assets}_{t-1}$	-8.96***	5.02***	0.52	0.58***	13.98***	1,348,040.00	18,374.00	77.00
	(-8.97)	(6.17)	(1.36)	(9.82)	(9.91)			

Table A.XIII: Standard Errors Robustness Check: Using Different Clusters

This table checks the validity of the standard errors in the baseline regression specification. Row 1 shows the baseline coefficients of the second-stage regression. The six “standard errors” rows show the standard errors under alternative clusters. The first five columns show the standard errors for each of the five dependent variables. The last four columns show the number of observations and the number of clusters in each regression (if applicable). Next to each standard error, the ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Model	*Estimates*					*Other Stats*			
	Log(PEN)	Log(USD)	Log(Total)	Ratio	Log(USD)-Log(PEN)	Obs	Firm Cl.	Month Cl.	Bank. Cl.
Baseline Coefficient	-24.30	16.29	3.38	1.42	40.58				
Standard Errors:									
(1) Baseline	7.06***	4.65***	1.55**	0.42***	10.86***	1,348,040.00	18,374.00	77.00	
(2) Firm	3.00***	2.71***	1.22***	0.20***	4.29***	1,348,040.00	18,374.00		
(3) Month	6.62***	3.97***	1.09***	0.38***	10.31***	1,348,040.00		77.00	
(4) Bank	5.39***	8.95*	2.58	0.55**	11.01***	1,348,040.00			12.00
(5) Bank and Firm	4.72***	7.44*	2.22	0.47**	9.28***	1,348,040.00	18,374.00		12.00
(6) Bank and Month	6.96***	7.87*	2.20	0.55**	12.30***	1,348,040.00		77.00	12.00

A Cross-Currency Basis Definition

In this section, I show that the general definition of *cross-currency basis* used in the literature, which is defined in dollar terms, is the same as the definition I use in this paper, but in soles terms.

Typically, the definition used in the literature for the cross-currency basis is

$$x_{t,t+n} = y^{\$}_{t,t+n} - y^{\$,fwd}_{t,t+n} \tag{A.1}$$

This definition is equivalent to the one I use in this paper (Equation (3), in Section 2). This is because the definitions of dollar- and soles-implied forward yields are

$$y^{\$,fwd}_{t,t+n} \approx y_{t,t+n} - \frac{1}{n} ln\left(\frac{F_{t,t+n}}{S_t}\right) \tag{A.2}$$

and

$$y^{fwd}_{t,t+n} \approx y^{\$}_{t,t+n} + \frac{1}{n} ln\left(\frac{F_{t,t+n}}{S_t}\right) \tag{A.3}$$

Therefore, my definition of *cross-currency basis* just regroups the literature's cross-currency terms:

$$\text{Literature:} \quad x_{t,t+n} \approx \quad y^{\$}_{t,t+n} - \overbrace{\left[y_{t,t+n} - \frac{1}{n} ln\left(\frac{F_{t,t+n}}{S_t}\right)\right]}^{y^{\$,fwd}_{t,t+n}} \tag{A.4}$$

$$\text{This paper:} \quad \equiv \overbrace{\left[y^{\$}_{t,t+n} + \frac{1}{n} ln\left(\frac{F_{t,t+n}}{S_t}\right)\right]}^{y^{fwd}_{t,t+n}} - y_{t,t+n} \tag{A.5}$$

B Setting: Macroeconomic Environment and FX Policies

Peru has a small, open economy; its flows in the forward market are largely determined by foreign investors. Peru's currency fluctuations are largely correlated with those of other emerging economies and the global strength of the dollar.

FX fluctuations concern policy makers in emerging economies because these economies, including Peru's, share a central characteristic: many of them are partially dollarized. For example, according to the Financial Soundness Indicators database (IMF), economies such as Paraguay, Uruguay, Poland, and Turkey had loan-dollarization rates of 47%, 56%, 22% and 39%, respectively, as of 2018. In these countries, these high rates of bank lending in foreign currency are explained by similarly high rates of foreign currency deposits from local agents. This means that firms and households borrowing in dollars from the local banking system can be particularly vulnerable to FX fluctuations since they are, for the most part, not hedged.

To limit FX risk, the Central Bank of Peru uses various tools that are common among emerging economies. These include hedging regulation, limits on carry trade flows/capital controls, and a combination of FX intervention by the Central Bank and changes in reserve requirements. In this section, I describe these tools, discuss how these are common in other economies, and show robustness checks that such policies do not affect the results of the paper.

1. Hedging Regulation. First, it is extremely common in other emerging economies for banks to have a regulation that allows them to have only very limited FX risk. For example, Canta et al. (2007) list more than 40 countries with such regulations; this type of regulation has also been discussed in other papers (e.g., Tobal (2018); Alfaro et al. (2022)). As in these other countries, Peru also has a regulation limiting banks' FX risk. Therefore, as shown in Figure A.1, banks unwind their forward positions in the spot market. However, since banks can have different positions in spot and forward as long as these fall below a threshold, this regulation does not prevent them from arbitraging CIP deviations. This is because arbitraging CIP deviations requires banks to offset forward and spot transactions, leaving the net spot-plus-forward position null. As I will explain later, however, as part of capital controls, in 2011, the bank regulator introduced limits to the forward positions of banks. This regulation differs from the hedging regulation studied in Keller (2020) in that it set a limit to the forward position alone, independently of the spot position.

2. Exchange-Rate Interventions. Second, several central banks intervene frequently in the exchange-rate market to smooth exchange-rate fluctuations and manage expectations (e.g., Mohanty and Berger (2013); Blanchard, Adler, and de Carvalho Filho (2015); Fratzscher, Gloede, Menkhoff, Sarno, and Stohr (2019); Candian, De Leo, and Gemmi (2023)). These practices have been common throughout history (e.g., Sarno and Taylor (2001); Fratzscher, Gloede, Menkhoff, Sarno, and Stohr (2019)), particularly at times of high volatility. Recently more countries have been intervening more frequently, such as Brazil, Chile, Colombia, and Turkey (Cavallino, 2019). Adler, Chang, Mano, and Shao (2021) have compiled a new dataset of exchange-rate interventions that shows the intensity of such interventions by a large number of countries. Peru falls only

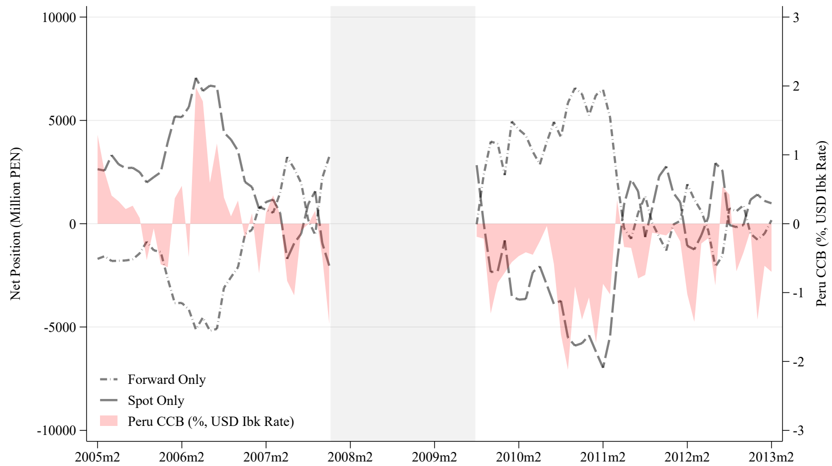

Figure A.1: Peruvian Banks' FX Positions

This figure plots Peruvian banks' aggregate spot and forward FX positions, and Peru's cross-currency basis. The dotted grey line is the banks' forward FX position. The dashed grey line is the banks' spot FX position. The red area is Peru's cross-currency basis computed using dollar interbank rates. All positions are presented in millions of soles. The shaded gray area represents the GFC. I am not showing these months, to prevent an outlier period from affecting the results and because the significant deviations affect the scale.

slightly above the median distribution across emerging economies, with a significant number of emerging and advanced economies intervening more frequently.

During my sample period, the Central Bank purchased an annual average of $6 billion (equivalent to 4% of GDP) and sold an annual average of $1.2 billion in order to mitigate exchange-rate volatility. These interventions impacted liquidity in dollars, but they had minimal effect on soles liquidity. This discrepancy arises because only the change in soles liquidity is sterilized.

3. Restrictions on carry trade inflows/capital controls. Third, because of the monetary policy trilemma, central banks cannot have independent monetary policy while at the same time controlling the FX and having free capital flows.

Amid a surge of capital flows, various countries decided to implement capital controls, also known as macroprudential policy tools. Evidence of this was seen during the Global Financial Crisis (GFC). At that time, when the United States decreased the dollar rate, a significant number of countries observed carry trade inflows. These inflows aimed at earning the interest-rate differential between the country they were investing in and the dollar. During this time, a new consensus emerged among economists regarding the implementation of capital controls on inflows.

A significant number of economists suggested that countries should adopt controls on inflows.[63] Several countries followed suit, including Brazil, Indonesia, Peru, South Korea, and Thailand.

Peru has a floating currency that has experienced important episodes of appreciation and depreciation. However, at such times, the Central Bank has intervened in the exchange-rate market to reduce these pressures and has implemented restrictions to reduce short-term capital flows. My sample period includes the aftermath of the GFC and therefore includes the restrictions on carry trade inflows described before.

As described in Keller (2020), these controls typically involve a series of regulations that affect money-markets as well as the forward markets. This is because various regulations are needed to block the two channels in which carry trade is done. One channel is borrowing dollars and buying soles short-term debt (bond channel). The second channel is buying soles against dollars forward (forward channel). In both cases, the foreign investor would receive the profits from an asset delivered in soles and a liability in dollars.

In Peru, as in various other emerging economies, the controls included (a) setting fees at 4% over notional to foreigners when purchasing soles certificates of deposit (CDs) of the Central Bank (implemented in early 2008), (b) limiting the amount of dollars banks can purchase in the forward market[64] (implemented in early 2011), and (c) setting 40% to 120% reserve requirements when local banks borrowed dollars from abroad (implemented in early 2008). Setting high fees on foreigners' soles bond purchases prevents carry trade through the bond channel. Limiting banks' forward holdings and making it costly for banks to borrow dollars limits banks' ability to absorb the flows coming from foreigners doing the carry trade through the forward channel.

The way these regulations limit carry trade flows is as follows. The fee foreign investors would need to pay to purchase sovereign short-term debt makes this channel unprofitable. This can induce foreign investors to perform the carry trade by selling dollars in the forward market.[65] Because

[63]See the change in stance of the IMF regarding capital controls at "IMF Adopts Institutional View on Capital Flows" in 2012. Also, more than 250 economists signed a letter voicing their support for such controls.

[64]See Keller (2020) for more details on the implementation of these controls as well as a detailed study of the effects of limits on banks' forward holdings.

[65]There are other reasons for foreign investors to prefer to do the carry trade in the forward market (via nondelivery forwards) rather than in the spot market. First, to trade in the spot market, they need to trade soles cash. For this, they need a bank account in Peru. This can add to transaction costs for foreign investors, as local banks in Peru already have bank accounts in soles. Second, the regulator of foreign investors is likely to consider Peru's short-term sovereign debt as risky and can add to balance-sheet costs (even in my sample period, which is before the introduction of Basel

local banks are market makers, they will buy dollars forward, but they need to sell them in the spot market to comply with hedging regulation.[66]

Selling dollars in the spot market requires banks to fund dollars. Here is where a second regulation on limiting carry trade flows, the high reserve requirements on foreign borrowing, kicks in. Setting high reserve requirements on foreign borrowing restricts banks from obtaining liquidity from abroad and increases banks' reliance on local dollar funding. However, dollars in the local market are constrained at this time. A combination of additional USD reserve requirements on local deposits and FX intervention by the Central Bank makes dollar funding scarce in the domestic market. As a result, banks can struggle to find dollar liquidity to hedge their long forward positions. This limits their absorption capacity in the forward market. And even when banks manage to find dollar liquidity, their absorption capacity in the forward market is further limited by the explicit limits to banks' forward positions.

4. Reserve requirements The Central Bank also imposes different reserve requirements in dollars and soles with the intention of changing liquidity in these currencies. This is also a common practice across central banks. In the sample period, these do not change often. When they change, dollars and soles move in the same direction. Broadly speaking, there have been two important discrete increases during carry trade inflows (early 2008 and July 2010). There was also a decrease in November 2008 due to the GFC.

B.1 Robustness of Results to Previous Regulations

This section performs robustness checks and shows that the previous regulations do not affect the conclusions of the paper.

As discussed before, Peru's Central Bank and bank regulator set regulations and intervene in the FX markets to reduce the volatility of the FX. Since we know the FX is correlated with CIP deviations (Section 5.4), and large swings in the FX also trigger a response of monetary and banking authorities, naturally CIP deviations will covary with the policies described earlier in this

III). This is less likely for banks operating in Peru. In addition to these disadvantages foreign investors face relative to local banks when trading local debt in Peru, local banks have other advantages, such as accessing primary auctions.

[66]While one could argue this could also be done in the forward market, during carry trade inflows, there is limited depth in the market with respect to those willing to take the other side of the trade.

section. Next, I describe how these affect the results. In sum, FX interventions help the mechanism outlined in this paper, while the rest have no effect on the conclusions of this paper.[67]

1. FX interventions. FX interventions could help enable the mechanism I propose here. When the currency required to do the arbitrage is scarce, CIP deviations can affect bank lending activities. However, I refrain from specifying why the currency required to do the arbitrage is scarce. One possible reason for this scarcity is the Central Bank's purchases of dollars. This limits banks' absorption capacity by making the currency required to do the arbitrage scarce.

There is no concern that the FX intervention will likely affect more the banks that arbitrage the most. This is because since they arbitrage more, they are more likely to be unwinding their forward positions in the spot market as part of the arbitrage. Whether the counterparty is the Central Bank or a different institution is of no importance. The result is the same. They need to perform the arbitrage, and hence will need to fund the spot position.

2. Local reserve requirements. My sample shows few changes in local reserve requirements.[68] This is shown in Figure A.2, which plots the changes in reserve requirements. The local reserve requirements in dollars are shown in blue. The local soles reserve requirements are shown in red for the base requirement, and in orange for the marginal soles requirement. Since I exclude the GFC, I observe only one important change in reserve requirements, which happened simultaneously in soles and dollars. This lack of variability makes it unlikely that reserve requirements affect my results. Moreover, my baseline regression also controls for lagged shares of soles and dollar deposits, which themselves are affected by the reserve requirements. Therefore, heterogeneous effects on banks coming from changes in reserve requirements should be controlled for.

Having said this, I still do various robustness checks. First, I compute CIP deviations using deposit rates adjusted by the cost of the reserve requirements. Table A.X, row (5), shows that this does not affect my results. Second, since a concern exists that reserve requirements may have affected more the banks that arbitrage the most, and thus explain my bank lending results, I perform a similar analysis to the one done for the correlation between CIP and FX. I find that changes in reserve requirements do not affect my results.

[67] I skip the implications FX hedging has on my results because I have already discussed how it affects the interpretation of the results in Section 3.1, Page 13.

[68] There were some during the GFC, but the GFC is not part of my sample.

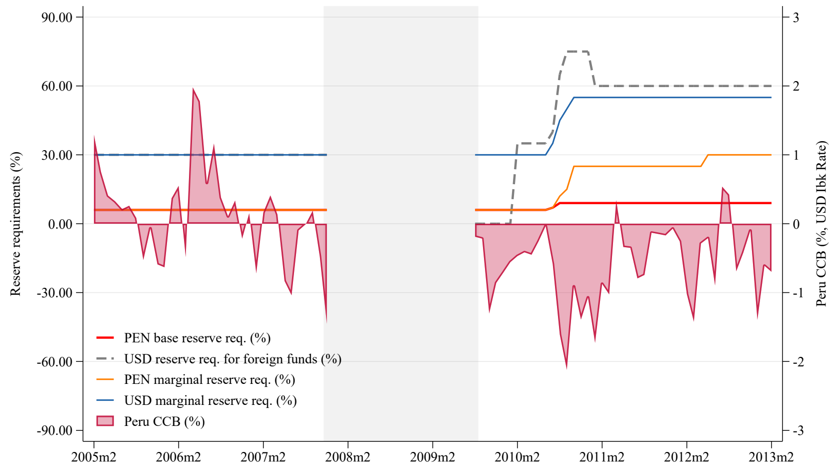

Figure A.2: Reserve Requirements vs. Peru's CCB

This figure plots the reserve requirements in PEN and USD, and Peru's cross-currency basis. The solid red line is the base reserve requirement in PEN. The dashed grey line is the reserve requirement for foreign funds in USD. The solid orange line is the marginal reserve requirement in PEN. The solid blue line is the marginal reserve requirement in USD. The red area is Peru's cross-currency basis. The shaded grey area marks the GFC.

If the reserve requirement is correlated with the basis, and the changes in the reserve requirement affect some banks more than others, one might worry that my results could be explained by changes in banks' liquidity coming from changes in reserve requirements rather than from arbitraging CIP deviations. Consider, for example, that banks with lower dependence on soles deposits are also the ones with higher betas. We know that as the basis decreases, the synthetic soles rate is lower than the cash soles rates, and banks profit from lending soles (and borrowing soles synthetically, which involves borrowing dollars cash). From the baseline regression, we know that as the basis decreases, banks with higher betas will also lend more soles. At the same time, assume the basis and the reserve requirements are negatively correlated. In this case, during times of lower basis, the reserve requirements are higher. Banks with lower dependence on soles deposits in terms of soles funding will be less affected by the higher reserve requirements and will therefore lend more soles than those with higher dependence on soles deposits.

Therefore, two different channels could yield similar results. One would be through the mechanism I propose in the paper on CIP deviations. The other would be through the reserve-requirement channel. One can carry out a similar analysis for dollars. If the correlation between the basis and dollar reserve requirements is negative, one would be concerned that banks with greater reliance on dollar deposits as a source of dollar funding are those with higher betas.

Indeed Figure A.2 shows that at the time of the increase in the reserve requirements, the cross-currency basis was more negative than the average during the time before the increase in requirements. This would imply that there is a negative correlation between the reserve requirements and the basis.[69] We know that for this to be a concern, banks with the lowest dependence on soles deposits as a source of soles funding should have higher betas. However, I do not find this to be the case. This can be seen in Panel A of Table A.XIV, which shows the summary statistics of the share of soles, dollars, and total deposits for banks with different arbitrage intensity, $\hat{\beta}$. Similarly, we can be concerned when banks with the highest dependence on dollar deposits as a source of dollar funding are also those with higher betas. Table A.XIV shows that this is marginally the case, but overall, the share of dollar and soles deposits across groups is very similar.

Table A.XIV: Summary Statistics: Local Reserve Requirements and Capital Controls

This table shows summary statistics of bank-level variables across the sample, split by arbitrage intensity ($\hat{\beta}$). The sample period is between February 2005 to February 2013, excluding the GFC.

	Low $\hat{\beta}$ $0 \leq \hat{\beta} < 0.2$		Medium $\hat{\beta}$ $1.6 \leq \hat{\beta} < 2.6$		High $\hat{\beta}$ $3.5 < \hat{\beta}$	
	Mean	Sd	Mean	Sd	Mean	Sd
$\hat{\beta}$	0.08	0.07	2.11	0.32	4.24	0.57
Panel A: Local Reserve Requirements						
Deposits Share						
PEN Dep/Liab	83.59	11.79	85.54	4.81	84.44	10.28
USD Dep/Liab	73.27	13.00	72.66	10.61	74.05	11.21
Total Dep/Liab	77.19	10.66	78.02	6.29	78.41	8.77
Panel B: Capital Controls						
(i) Foreign Reserve Requirements						
USD Foreign Liab/USD Liab	3.97	3.92	6.82	4.86	9.60	9.31
USD Foreign Liab/Total Liab	2.02	2.50	4.10	2.94	5.72	5.64
(ii) Forward Limits						
% Use at Announcement	2.29	0.69	105.62	35.54	78.27	22.66
% Use (sample)	1.59	2.81	10.72	47.77	34.03	48.89

Since I find that banks with higher betas also depend marginally more on dollar deposits as a source of funding, I perform a robustness check similar to the one I do for FX rates. In the regression on bank lending, I add to the baseline regression the interaction between the $\hat{\beta}$

[69] This is expected. In the paper, I discuss how the basis is negatively correlated with carry trade inflows. These inflows occur during periods of economic growth in Peru, and this is when the Central Bank increases reserve requirements.

and $\frac{\text{deposits in `y' currency}}{\text{total liabilities in `y'}}$, where *'y' currency* is the currency of the dependent variable. Panel A of Table A.XV shows that the change in the reserve requirement does not affect my results.

Table A.XV: Baseline Results After Controlling for Domestic Reserve Requirements and Capital Controls

All specifications, unless noted otherwise, use the same fixed effects (firm-month and bank-month) and lagged bank controls as those used in the baseline specification. Row 1shows the baseline coefficients. The dependent variables in logarithm have been multiplied by 100. The ratio of dollar to total loans is expressed on a 0–100 scale. T-statistics are in parentheses. Standard errors are from the joint estimation with the first stage and are clustered by date and firm. ***, **, and * denote significance at 1%, 5%, and 10%, respectively. The sample period is from February 2005 to February 2013, excluding the GFC. To prevent the results of the dollar loans from reflecting changes in the exchange rate, I have converted these loans to soles using a constant exchange rate (corresponding to February 2005).

	Log(PEN)	Log(USD)	Log(Total)	Ratio	Log(USD)-Log(PEN)
Panel A: Domestic Reserve Requirements					
$\text{CCB}_{t-1} * \hat{\beta}$	-24.11***	16.36***	3.39**	1.57***	44.75***
	(-3.37)	(3.51)	(2.18)	(3.26)	(3.58)
PEN Deposits/ PEN $\text{Liab}_{t-1} * \hat{\beta}$	0.05			0.03**	0.86**
	(0.63)			(2.18)	(2.33)
USD Deposits/ USD $\text{Liab}_{t-1} * \hat{\beta}$		-0.00***		-0.00**	-0.01***
		(-7.47)		(-2.53)	(-2.70)
Total Deposits/ Total $\text{Liab}_{t-1} * \hat{\beta}$			-0.00***		
			(-3.42)		
Panel B.1: Capital Controls: Foreign Reserve Requirements					
Regression 1					
$\text{CCB}_{t-1} * \hat{\beta}$	-24.33***	16.30***	3.38**	1.42***	40.63***
	(-3.42)	(3.49)	(2.18)	(3.37)	(3.72)
USD Foreign Liab/ Total $\text{Liab}_{t-1} * \hat{\beta}$	0.22	-0.10	-0.03	-0.02	-0.33
	(0.79)	(-0.53)	(-0.34)	(-1.23)	(-0.78)
Regression 2					
$\text{CCB}_{t-1} * \hat{\beta}$	-24.32***	16.29***	3.38**	1.42***	40.61***
	(-3.42)	(3.49)	(2.18)	(3.37)	(3.71)
USD Foreign Liab/ USD $\text{Liab}_{t-1} * \hat{\beta}$	0.15	-0.04	-0.01	-0.01	-0.19
	(0.85)	(-0.31)	(-0.23)	(-1.03)	(-0.71)
Panel B.2: Capital Controls: Forward Limits					
Regression 3					
$\text{CCB}_{t-1} * \hat{\beta}$	-23.83***	16.42***	3.58**	1.41***	40.26***
	(-3.53)	(3.54)	(2.26)	(3.46)	(3.81)
% Use Fwd $\text{Limit}_{t-1} * \hat{\beta}$	-0.05	-0.01	-0.02***	0.00	0.04
	(-1.66)	(-0.89)	(-3.13)	(0.44)	(0.83)
FE					
Firm $*$ Date FE	Yes	Yes	Yes	Yes	Yes
Bank $*$ Firm FE	Yes	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes	Yes
Observations					
Firm Cluster	18,374	18,374	18,374	18,374	18,374
Month Cluster	77	77	77	77	77
Number Obs	1,348,040	1,348,040	1,348,040	1,348,040	1,348,040

3. Restrictions on carry trade inflows/capital controls Since restrictions on carry trade inflows and capital controls on inflows involve various restrictions, I analyze each of these. First, capital controls include a restriction on foreign investors' purchases of the Central Bank's CDs. This restriction can shift foreign investors' demand for soles forward, and with this, the amount banks can arbitrage. However, this restriction does not affect bank lending, except through the mechanism I describe in this paper. That is, by changing banks' ability to arbitrage. Therefore, since this restriction does not involve an alternative channel correlated with banks' arbitrage that can explain bank lending, this restriction is not a threat to the validity of my results.

Second, capital controls also include high reserve requirements when borrowing dollars short-term from abroad. For my results to be valid, this requirement should not affect my results from a channel other than banks arbitraging CIP deviations. This is likely because the requirement has changed little during my sample period (as shown by the dotted gray line in Figure A.2). However, out of caution, I also try to rule out the possible confounder that some banks lend less in dollars when the basis decreases because of the higher foreign-reserve requirements rather than arbitraging the basis. To do so, I take an approach similar to the one used to analyze the possible FX and local reserve-requirement confounders.

As in the case of local reserve requirements, one could be concerned that some banks use foreign funds that have been subject to the higher reserve requirement after 2010 to lend. Since the increase in such reserve requirements happens at a time when the basis is negative, the possible heterogeneous effect of this reserve requirement on banks could in principle explain my results. This would be problematic if the high-arbitrage banks are also those that depend more on this funding for lending purposes. Since, as seen in Panel B, Part (i) of Table A.XIV, high-arbitrage banks use more of this funding, we cannot easily rule out the alternative mechanism of higher reserve requirements affecting lending of high-arbitrage banks through a different channel that is not arbitrage.

However, the correlation between $\hat{\beta}$ and this type of funding is expected if this funding was used to arbitrage (and hence the Central Bank set high requirements on these funds to prevent such arbitrage). An indication of this could be that the basis is negatively correlated with this type of borrowing. And it is: ($\rho = -0.3547$). As the basis decreases and the soles synthetic rate is lower than the cash rate, banks borrow more in dollars from abroad. This is what is needed to arbitrage the basis, as banks need to borrow in the soles synthetic rate, which implies borrowing dollars.

To alleviate these concerns, I check whether the bank-lending results would be affected by introducing into the regression the interaction between the share of dollar foreign liabilities and arbitrage intensity. This is shown in Panel B, part (i) of Table A.XV. I find my baseline results are robust.

Finally, in January 2011, as part of restricting capital inflows, the Central Bank imposed limits on banks' purchases of dollars forward. Keller (2020) shows that this regulation affected bank lending.[70] While Keller (2020)'s results are consistent with the ones in this paper, they do not explain the results here. First, Keller (2020) focuses only on the reaction to the announcement of capital controls on a limited sample. This paper, in contrast, looks at a larger sample. Second, as shown in Table A.XIV, the banks mostly affected by the capital controls (the treated banks in Keller (2020)) are not the ones that arbitrage the most here. Hence, the results in this paper are coming from a different source. Finally, the imposition of capital controls cannot explain the co-movement between banks' arbitrage and the basis. I also add the interaction between the lag of the percentage use of forwards, activated after the limit is imposed, and the arbitrage intensity, and I find that the baseline results are also not affected (see Panel B, part (ii) of Table A.XV).

C Market Segmentation

In Peru, as in many emerging markets, the local banking system has an advantage when trading its local currency and money-market instruments. This is, in part, a result of market segmentation in the exchange rate and money-market instruments to which local banks have access but other market participants, such as foreign banks, do not. Below, I detail the advantages of local banks over other investors in arbitraging the CIP deviations that arise from market segmentation.[71]

[70] Keller (2020) shows that at the time of the announcement, some banks were above the forward limit. They had three months to liquidate such positions and be within the limits. Since the forward positions of banks are hedged, as banks reduced their long forward positions, they increased their long dollar spot positions. This meant increasing dollar assets and reducing soles liabilities. As such, banks that were more affected by the regulation (i.e., those above the limit), increased their lending in dollars and decreased their lending in soles by more than banks less affected by it.

[71] There are other advantages too. One is having a soles deposit base. Another is that regulators in developed economies might consider emerging economies' sovereign securities as risky and apply risk-weight factors to foreign banks purchasing these securities. In contrast, regulators in emerging economies might consider the sovereign debt of the country as risk-free.

Central Bank primary auctions. In contrast to foreign banks and to most nonbank domestic participants,[72] local banks have access to the Central Bank's primary auctions. These include, among various other instruments, CDs in soles as well as repos. The CDs and repos are at the core of arbitraging CIP deviations. Without access to the primary auction, foreign banks and other domestic participants are constrained to trading CDs in the secondary market. This allows local banks to charge a premium.

In addition, local banks can always deposit any excess soles and dollars at the Central Bank, using the overnight Central Bank deposits. Any balance in excess of that required to satisfy the reserve requirement in each corresponding currency is taken as a dollar deposit at the Central Bank. In soles, the deposit rate is established in conjunction with the soles target rate after its monthly monetary policy meeting. In dollars, the Central Bank publishes the rate on a daily basis to local banks. This rate was a function of the Libor (during my sample period), and now of the secured overnight funding rate, SOFR. However, the exact calculation is not public information.

Interbank USDPEN spot market. In addition, only local banks have access to the interbank spot exchange-rate market. That is, only local banks have access to the trading platform for the interbank spot market, which is where most interbank spot trades are conducted and the reference "live" price for the USDPEN. This difficulty is not only present in Peru. Foreign investors also have difficulties accessing the spot market in Chilean pesos, so local banks are the ones conducting the arbitrage in Chile (Aldunante et al., 2022).

Additional constraints on foreign investors at different points in time. The market segmentation in money-market and spot transactions described before is a general description that applies to all my sample. However, there have been times in which this segmentation has been even stronger.

First, there have been times in which the Central Bank has mostly issued term deposits or only issued CDs that can only be negotiated among local banks.[73] This was specifically done to prevent foreigners from purchasing these CDs at times of capital inflows when foreign investors wanted to purchase such CDs (Central Bank of Peru, Inflation Report, 2010). That is, even in the

[72] The participants authorized to trade certificates of deposit (CDs) in primary auctions and repos are described in "circulares" the Central Bank publishes on its website for each of the different CDs it issues (the various types include fixed rate, floating rate, and liquidated in USD).

[73] Examples of these types of deposit include CDBRP-NR (i.e., "certificate of deposit with restricted negotiation"), CDLD (a CD bought with US dollars but that gives a soles return), and CDV (CD with a variable rate).

secondary market, these instruments can only be traded among local banks. This restricts the set of possibilities in which foreign banks (or other investors) can invest short term in soles to do the arbitrage. This is especially important because the times in which these instruments are in most demand — to arbitrage negative CIP deviations — are when the Central Bank issue more of these CDs with restricted access.[74]

Second, at times with important carry trade inflows, such as at the end of 2007 and early 2008, the Central Bank imposed a transfer fee when foreign institutions buy the Central Bank's CDs in the secondary market. The transfer fee was 4% of the notional value in January 2008, eliminating any carry trade and CIP arbitrage that foreign investors could have.[75] Since this fee is not applicable to trades among local banks, they can obtain arbitrage profits that foreign banks cannot.

At this point, one could imagine that local banks and foreign investors could work around this restriction. Foreign banks could give funds to local banks to invest in the CDs. At the end of the term, local banks could provide the return to foreign banks. Indeed, starting in February 2008, when the aforementioned 4% fee was set, foreign investors increased soles-linked deposits in local banks. However, just two months later, the Central Bank set a 120% reserve requirement on any borrowing from foreign investors — by May 2008, these deposits had dropped by more than 70% (Central Bank of Peru, Nota Informativa, 2008). This made this intermediation also very costly.

Similar restrictions on capital inflows were set in various other emerging economies at the same time.

D Sample Restrictions: Regulations After 2013 and Robustness

My sample period is February 2005 to February 2013. After this date, two regulations were enacted that contaminate the main variables of my analysis. These regulations coincide with a 40%

[74]This is because the times in which the cross-currency basis is negative is when foreign investors want to do the carry trade. The Central Bank wants to restrict foreign investors, because they worry about "speculative flows" affecting the exchange rate.

[75]The regulation can be found on the Central Bank's website, at: https://www.bcrp.gob.pe/docs/Transparencia/Normas-Legales/Circulares/2008/Circular-006-2008-BCRP-Comisiones.pdf

depreciation of the sol that occurred from the taper tantrum in 2013 up to 2016.[76] Since various firms were borrowing in dollars, there were important financial losses for these firms (Humala, 2019). Other emerging-market economies also implemented similar regulations around this time, probably due to similar depreciation losses incurred by companies that had liabilities in dollars.[77] Below I summarize these regulations.

1. Regulations on the lending market. In March 2013, the Central Bank started a program to reduce banks' dollar lending. It required banks to pay additional reserve requirements over their dollar liabilities if they surpassed certain thresholds. When this program started, it targeted only mortgages and car loans. In October 2013, the program expanded to all types of loans.

Initially, the thresholds allowed for limited dollar credit growth. However, in December, the thresholds implied a reduction in banks' stocks of dollar debt. Therefore, to avoid having to pay additional reserve requirements, banks would need to substitute a share of their balances of dollar lending for soles. To enable banks to substitute part of the balances of dollars lent to soles, the Central Bank started to provide funding in soles, using as collateral banks' dollar deposits. This was particularly important: given the depreciation of the sol during this time, households and firms shifted part of their soles deposits to dollars.[78]

2. Regulations on the forward market. In response to the significant depreciation of the sol after the taper tantrum, in addition to the de-dollarization policies described before, in January 2015, the Central Bank also introduced reserve requirements to banks' sales of dollars in the forward market. The Central Bank argued this was to limit "speculation" from foreigners and because this is where

[76]There is an important difference in sample and context compared to Gutierrez, Ivashina, and Salomao (2023), whose sample starts from 2013. Since the economic outlook differs significantly during their sample, the behavior I observe in my sample differs from theirs.

[77]For example, India set additional provisioning and capital requirements on banks when lending to firms with unhedged currency mismatches. Indonesia set regulations at the end of 2014, forcing firms to hedge at least 20% of their unhedged foreign liabilities that are due in the near term. Turkey also introduced regulations on corporate foreign currency borrowing, although these came later, in 2018. For India's regulation, see Reserve Bank of India, Capital and Provisioning Requirements for Exposures to Entities With Unhedged Foreign Currency Exposure, at: https://www.rbi.org.in/scripts/NotificationUser.aspx?Id=8694&Mode=0. For Indonesia's regulation, see KPMG, Prudential Principles for Offshore Borrowing, at: https://assets.kpmg.com/content/dam/kpmg/pdf/2016/07/id-prudential-principles-offshore-borrowings.pdf. For Turkey's regulation, see Central Bank of Turkey, New Foreign Exchange Restrictions in Turkey: Why and How?, at: https://www.lexology.com/library/detail.aspx?g=41336a71-1abf-4141-8ae9-738a76994e17

[78]This funding took the form of various types of repos. One of these was only to substitute banks' dollar balances. Others were to allow banks to expand their soles lending.

the depreciation pressure on the sol was coming from.[79] These reserve requirements applied when banks surpassed specified daily, weekly, and balance position limits and became progressively stricter during 2015.[80]

In addition to this new regulation, there was also another change in the forward markets. Starting from October 2014, with the same purpose of mitigating the depreciation of the sol, the Central Bank started selling dollars with foreign-exchange-rate swaps (FX swaps), instead of selling in the spot market as they had done before. The Central Bank's October 2014 Inflation Report describes that they used this instrument to sell dollars without affecting its international reserves and without affecting the soles liquidity in the banking system.

To sum up, various restrictions and new policy interventions occurred after the taper tantrum that affected both my outcome variables and my explanatory variables. To prevent my results from being affected by such regulations, which also caused outliers in CIP deviations, I decided to exclude the sample after 2013 from my analysis. Though the taper tantrum occurred after May 2013, I decided to end the sample in February 2013 to have complete years from the start of my sample (February 2005, the start of the credit-registry data I was given). The results are robust to changing to ending the sample in April 2013.

E Explanations for Arbitrage Heterogeneity

An underlying question is why some banks are able to arbitrage more than others. One possible set of explanations includes constraints on the balance sheet. That is, banks with more constraints

[79] See Gestion, "BCR tomara medidas agresivas para restringir credito en dolares en 2015" (December 17, 2014) at: https://gestion.pe/impresa/bcr-tomara-medidas-agresivas-restringir-credito-dolares-2015-87287-noticia/; and Gestion, "Medidas mas potentes del BCR podrian frenar alza del tipo de cambio" (August 27 2015) at: https://gestion.pe/impresa/medidas-potentes-bcr-frenar-alza-tipo-cambio-98377-noticia/

[80] These limits differ from those implemented by the Bank Regulator in 2011. First, the Central Bank had daily, weekly, monthly, and balance limits on banks' sales of dollar forwards, while the Bank Regulator limited only the net forwards' balance. Second, the Central Bank does not impose a hard limit on forward transactions, as the Bank Regulator does. Hence, banks could decide to surpass the Central Bank limits (which are lower than those of the Bank Regulator) and pay a cost for doing so. Third, the Central Bank limits are on banks' *sales* of dollar forwards (on a daily, weekly, monthly, and balance basis). In contrast, the limits implemented by the Bank Regulator apply to the *net* position of forwards. Hence, the Bank Regulator's limit implies that banks can have large sales of dollar forward positions as long as these are compensated by purchases of dollar forwards. The Central Bank's limits would not allow that, as they consider only the sales of dollar forwards without any netting. Finally, the Central Bank limits are also more binding than those of the Bank Regulator regarding the balance.

on their balance sheet arbitrage less. Another possible set includes the type of client in the forward market.

Below, I present correlations to show suggestive evidence of potential explanations. One important limitation, however, is that explaining the cross-section of banks is difficult because there are only few banks, meaning regressions at the bank level lack observations to draw deeper conclusions.

While constraints to the balance sheet can be a reason for banks to differ in the degree they arbitrage, it might not be the only reason. For example, banks that have clients whose demand on the forward market goes against market flows could be more likely to arbitrage to a greater extent. This is because these clients offer banks an opportunity to unwind part of their forward position in case they need to. Therefore, they could be more confident in taking larger arbitrage positions if they know they can easily liquidate them if needed.

Banks have various incentives to unwind. First, they may have limited funding capacity to arbitrage CIP deviations, and, if they expect these deviations to amplify, they might want to liquidate previous positions to make room for more profitable arbitrages. Second, if they have maturity mismatches between their forward contracts and their funding, and if their funding is becoming more expensive, they might want to close forward positions (and hence spot positions). Third, after limits on forward contracts, they might have limited capacity to buy new contracts and they could want to unwind part of their position. These are only three examples of situations in which banks value having a vast set of clients who enable them to unwind their positions. There could be additional reasons.

I find evidence that suggests that banks arbitrage more when they think they can count on clients with whom to unwind positions.[81] In my sample, on average, banks' forward positions have been long dollars forward (i.e., clients are selling dollars forward). If the premise that banks value having clients with offsetting flows is valid, then banks that have greater arbitrage sensitivity to changes in the basis (have higher $\hat{\beta}_b$) should be those with a greater share of clients who trade relatively often — and that when they do, they buy dollars forward. This indeed is what I find. Panel A, Figure A.3 shows the fit line of $\hat{\beta}_b$ against each bank's share of clients buying dollars forward.

[81] This excludes local banks.

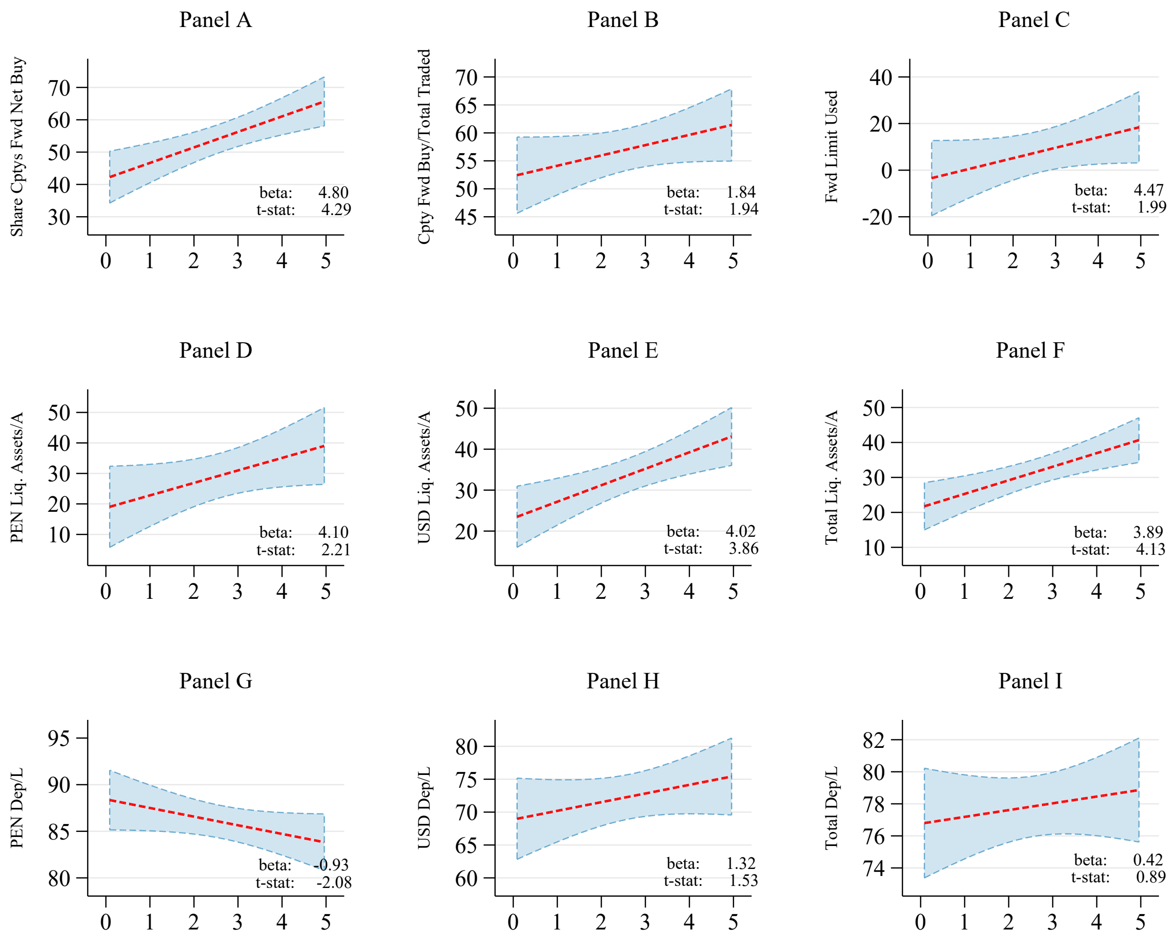

Figure A.3: Arbitrage Intensity and Bank Indicators

The x-axis for all panels is $\hat{\beta}_b$. The dependent variable for each panel (y-axis) is as follows. Panel A: share of clients buying dollars forward. Panel B: share of clients' dollar buy transactions over total transactions. Panel C: forward limit used. Panel D: PEN liquid assets over assets. Panel E: USD liquid assets over assets. Panel F: total liquid assets over assets. Panel G: PEN deposits over liabilities. Panel H: USD deposits over liabilities. Panel I: total deposits over liabilities. All dependent variables are in %, on a 0–100 scale. For Panels A and B, I compute, for each bank, the average among their clients. For Panels C to I, I compute, for each bank, the average over time for each variable. I then regress these on beta. The red line is the line of best fit. The shaded blue area is the 95% confidence interval. The sample period is from February 2005 to February 2013, excluding the GFC.

To compute this share, I first restricted the sample of clients to those that traded frequently (at least 38 times during the 77-month sample[82]). Second, I classify each client as either a *net buyer* or a *net seller*. This classification comes from netting all of their forward transactions across my sample. If in net they bought dollars forward, then the client is a buyer; if not, the client is a

[82] 77 months comes from 96 months minus the length of GFC

seller. Third, with this classification, I map each client to banks that traded at least once with said client. The assumption is that each counterparty that traded with a bank in any of the 77 months of the sample is a potential client with whom banks could trade and unwind part of their position (particularly because I restrict the sample to those trading relatively often). Finally, I compute each bank's share of net buyer clients as the ratio between the sum of all of the bank's clients who bought in net during the sample and their total number of clients.

I validate the interpretation of the previous variable by computing alternative measures that can capture banks' ease of unwinding their long dollar forward positions. For example, this relationship also holds when comparing banks' $\hat{\beta}_b$ with their client's average share of dollars bought (i.e., dollars bought/total negotiated). This is shown in Panel B, Figure A.3 . Furthermore, these coefficients presented are tilted downwards by banks that do not trade much (banks with $\hat{\beta}$ very close to 0). Conditional on being a bank that trades more often ($\hat{\beta}$ >0.5), the relationships become significantly stronger. An increase in 1 of $\hat{\beta}$ is associated with an increase of 2.5 percentage points in the clients' average share of dollars bought. This result is statistically significant.

While the above suggests that other factors beyond balance-sheet constraints could explain arbitrage heterogeneity, it is likely that balance-sheet constraints play a role. Precisely, the variables that likely constrain banks from arbitraging include restrictions on funding and being close to a capital-controls limit — this includes a limit, established in 2011, on the amount banks can buy in the forward market.

Constraints to arbitrage coming from banks' balance sheets are more endogenous to banks' arbitrage actions than banks' counterparties.

The endogeneity of constraints to arbitrage, such as liquidity variables and the percentage use of the forward limit, pose some challenges. First, one can learn less about a regression specification of rolling betas against these variables because of inverse causation. With enough autocorrelation, even lagged variables could be contaminated by inverse causation. Second, regressions adding various covariates may not be informative. All covariates could be affected by the arbitrage itself. Therefore, it is hard to disentangle the correlation between a variable and $\hat{\beta}$. This seems to be the case.

The results from using month fixed effects and regressing 12-month rolling $\hat{\beta}$ regressions on 12-months lagged of the 12-month moving average of liquidity, deposit variables, and forward limits[83] shows that no variable, except dollar and soles shares of liquid assets, is statistically significant. These results are not stable, and they vary when running contemporaneous regressions. Those results also differ from the ones obtained from Figure A.3 and the $\hat{\beta}_b$ rolling regressions that regress one variable at a time, where all, except dollar deposits, are statistically significant.

Given this, my analysis is restricted to fit plots of the correlation between $\hat{\beta}$s and the bank-level averages of various liquidity variables, and the use of forward limits. These fit plots are displayed in Figure A.3. In line with the argument that liquidity is important to execute the arbitrage, the plots show that banks with higher $\hat{\beta}$s have more soles and dollar liquid assets. I also find that they have more dollar deposits (as a share of total liabilities). This is consistent with the sign of the CIP deviations. In my sample, CIP deviations have been mostly negative. In this situation, banks require mostly dollar funding. Therefore, banks with higher $\hat{\beta}$s have a higher share of dollar deposits but not a higher share of soles deposits as a fraction of total liabilities.

[83]The exact regression is:

$$\begin{aligned} \text{12mo } \hat{\beta}_b \text{ rolling}_{bt} = {} & \gamma_1 \text{FwdLimUsed}^{\text{MA 12m}}_{b,t-12} + \gamma_2 \text{PENLiqA/A}^{\text{MA 12m}}_{b,t-12} + \gamma_3 \text{USDLiqA/A}^{\text{MA 12m}}_{b,t-12} \\ & + \gamma_4 \text{PENDep/L}^{\text{MA 12m}}_{b,t-12} + \gamma_5 \text{USDDep/L}^{\text{MA 12m}}_{b,t-12} + \text{Month-FE} + \varepsilon_{bt} \end{aligned}$$

where 12mo $\hat{\beta}_b$ rolling is the estimated $\hat{\beta}_b$ using 12-month rolling regressions for each bank. All covariates are a 12-month moving average (to coincide with the 12-month rolling $\hat{\beta}$, lagged 12 months. This means that the covariates are computed over a window that does not coincide with the rolling $\hat{\beta}$. The covariates are as follows. FwdLimUsed is the percentage utilization of the forward limit. This variable is zero before its imposition, in January 2011. PENLiqA/A and USDLiqA/A are the share of liquid assets (over assets) of the corresponding currency. PENDep/L and USDDep/L are soles and dollar deposits as a share of total liabilities.