Arbitraging Covered Interest Rate Parity Deviations and Bank Lending

LORENA KELLER [a]

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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 there are CIP deviations, banks attempt to arbitrage them. This requires banks to borrow in a particular currency. When this currency is scarce, banks shift resources away from lending to fund their arbitrage activities. Then, bank lending in the currency required to arbitrage decreases. I test this channel by exploiting differences in the abilities of Peruvian banks to arbitrage CIP deviations and find evidence that supports the proposed channel.

[a] The Wharton School, University of Pennsylvania. E-mail: lorenak@wharton.upenn.edu. I am indebted to the Peruvian Superintendencia de Banca y Seguros (Peruvian bank regulator - SBS) and the Superintendencia Nacional de Administración Tributaria (Office of income tax collection - SUNAT) for their collaboration in providing and collecting the data. I am very grateful to Santiago Medina for excellent research assistance. This project has greatly benefited from very helpful comments from Manuel Amador, Jules van Binsberger, Andres Drenik, Wenxin Du, Umang Khetan, Michael Roberts, Nikolai Roussanov, Adrien Verdelhan. It has also benefited from seminar participants at FMA, George Washington University, NYU Stern, University of Texas at Austin, Wharton, Wisconsin-Madison, NBER Summer Institute (International Asset Pricing), SED, Rome Junior Finance Conference, WFA. I am also very 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 (FX) forward and swap contracts. However, as documented by Du, Tepper, and Verdelhan (2018), there have been important deviations in developed economies that do not stem from outlier events occurring during the financial crisis. Although for different reasons and with a different dynamics, these deviations also exist in emerging economies. In this paper, I show that these deviations can affect banks' decisions on the currency composition of their lending in an emerging market setting.

I start by proposing a channel through which CIP deviations can affect bank lending in a partially dollarized economy. The channel is as follows. CIP deviations imply that there are arbitrage opportunities. When these deviations exist, banks, who are the natural CIP deviations arbitrageurs, attempt to arbitrage them.[1] However, the arbitrage requires banks to borrow a particular currency. When funding in that particular currency is scarce, banks need to either increase rates paid on deposits or shrink funds in that currency that are being used in other activities, such as lending so that these funds can be used 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 required to arbitrage is likely going to decrease relative to the one that is not required to arbitrage. Hence, arbitraging CIP deviations can contribute to changes in currency mismatches in partially dollarized economies.

I test this channel by studying the relationship between arbitraging CIP deviations and bank lending in Peru during a non-crisis period. I proceed in three complementary steps. First, I show that banks' FX 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. Finally, I exploit that banks have different arbitrage-sensitivities to CIP deviations to show that banks that arbitrage more shift more the currency of their lending in accordance to what is profitable to arbitrage.

The first step of the empirical analysis relies on how CIP arbitrage is executed. This is best explained by reviewing first the CIP condition. Consider a local bank in Peru which has the

[1] Although banks cannot arbitrage them fully as else there would not exist CIP deviations.

opportunity to lend 1-month at the risk-free rate in dollars or in soles, the Peruvian currency. Under CIP, the return of lending soles directly should equal the return of lending dollars and simultaneously hedging the FX risk by selling dollars forward to convert them back to soles. The return of the combination of lending dollars and hedging the FX is the soles synthetic rate. The difference between the soles synthetic rate and the cash rate of lending directly is the cross-currency basis. This basis measures the deviations from CIP.

Based on this description, the first step of the empirical analysis consists of measuring both at the aggregate and at the bank level whether banks' transactions are consistent with the expected trades needed when banks arbitrage CIP deviations. In Peru, during my sample, CIP deviations have oscillated between -2% and 2% (excluding the financial crisis). When the cross-currency basis increases and the soles synthetic rate is greater than the soles cash rate, banks could theoretically profit from borrowing soles in the money market and lending them synthetically. This entails four transactions: (i) borrowing soles, (ii) selling soles and buying dollars spot, (iii) lending those dollars, (iv) hedging the FX by selling dollars forward.

I use confidential data from Peru to show that as the cross-currency basis increases, banks engage in more of each of these four transactions. These are only correlations but suggest that banks' transactions are consistent with arbitraging CIP.[2] From the FX side, I have all of the forward contracts of all banks in Peru. I also have all of their daily spot transactions. Using these two datasets, I show that both in aggregate and at the bank level, banks buy more dollars spot and sell more dollars forward as the cross-currency basis increases. From the money market side, I also see banks' interbank loans, financial obligations and investments. As expected, as the cross-currency basis increases, banks borrow more soles and invest more dollars.

I complement the analysis with confidential information that has daily bank-level interest rates paid on bank deposits. With this data, I find that as the cross-currency basis increases, banks also increase the spread paid on soles term deposits, while they reduce this spread on dollar term deposits. I also find that the bank's soles liquid assets decrease and dollar liquid assets increase as the cross-currency basis increases. This suggests that there is scarcity in the currency required to be

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

funded to arbitrage CIP deviations. Yet, despite the scarcity of funds to arbitrage CIP deviations, banks seem to allocate funds to arbitrage these deviations.

While I find that banks' transactions are consistent with arbitraging CIP deviations, I also find that banks differ significantly in terms of how much they respond to these deviations. I find that after a 1pp increase in the USDPEN cross-currency basis, some banks respond by allocating approximately 4% more of their assets to perform the arbitrage, while some others barely respond. Because this heterogeneity is helpful when analyzing how arbitraging CIP deviations can affect bank lending, I construct a bank-specific measure of banks' ability to arbitrage CIP deviations. This measure looks at how much each bank changes its forward position that is matched with offsetting spot positions -two transactions required to arbitrage CIP deviations- after an increase in the cross-currency basis.

I use this bank-specific measure on banks' abilities to arbitrage CIP deviations to analyze the possible impact of arbitraging CIP deviations on bank lending in soles and dollars. To reduce the influence of shocks to the Peruvian economy that correlate with CIP deviations in Peru and bank lending and to mitigate concerns that particular hedging choices of banks affect the cross-currency basis, I instrument the USDPEN cross-currency basis with that of Mexico and Chile. Exploiting the heterogeneity in banks' abilities to arbitrage CIP deviations, I use a within firm-month analysis to show that banks that allocate 1pp more of their assets to arbitraging CIP deviations increase their dollar lending relative to soles lending by 11 to 40%[3] after a 1pp increase in the USDPEN cross-currency basis instrument. This increase in the difference between dollar and soles lending is due to both, an increase in dollar lending and a decrease in soles lending. These results stem from simultaneously comparing: (i) the lending of the same bank to the same firm at different levels of CIP deviations and (ii) the lending of high arbitrage-intensive banks relative to less arbitrage-intensive ones.

Comparing lending across banks with different arbitrage abilities is one of the ways I use to try to alleviate the endogeneity problems that arise when trying to link arbitraging CIP deviations to bank lending. Because CIP deviations are endogeneous, they correlate with macroeconomic

[3] 11% is the most conservative estimate I obtained, which holds when restricting the sample to firms borrowing in soles and dollars. When including the possibility of firms switching currencies, the estimates increase to 40%.

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 on the same month controls for changes in economic conditions that affect all banks.

However, banks are heterogeneous and therefore shocks might not affect them in the same degree. I take three steps to mitigate this problem. The first one is to use lagged bank controls to control for bank heterogeneity in their balance sheets.[4] The second one is to provide robustness checks that narrow the analysis to the most similar banks. In this subset of banks, I analyze whether those that arbitrage more lend more in dollars and less in soles as the basis increases. I find this is still the case. Finally, the third step I take is to focus on whether the correlation between the FX and CIP deviations affects the results.[5] I refer to this channel as the FX channel. In Peru, the value of the dollar is positively correlated with the cross-currency basis. As the sol depreciates, it is expected that agents change their deposits from soles to dollars. This itself generates a shortage of funding for banks in soles relative to dollars. Therefore, through independent channels, banks could decide to lend less in soles and more in dollars as the cross-currency basis increases and the sol depreciates.

Although it is very likely that the FX channel is at play, I show that this channel is likely not the one behind the results on bank lending. If the FX channel described before explains the results on bank lending, it must be that the depreciation of the sol affects more the banks that have greater ability to arbitrage. That means that banks with greater ability to arbitrage also face greater reduction of soles deposits when the currency depreciates and therefore end up lending more in dollars relative to soles as the cross-currency basis increases and the sol depreciates. I do not find evidence for this. The banks that arbitrage the most are not those experiencing greater reduction in their soles and increase in dollar deposits after the currency depreciates. Moreover, controlling for the possible differential effect in FX does not change the results.

Related to the FX channel, one could be concerned that changes in the FX change the demand for loans of firms that have foreign trade. However, I do not find that changes in the demand for

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

[5]This correlation is the only one I am aware that can affect the results. This correlation was established in Avdjiev, Du, Koch, and Shin (2019).

loans of firms with foreign trade drive the results. I find that taking out these firms from the sample yields similar results.

The results presented in this paper are robust to a series of alternative specifications, such as using alternative measures of CIP deviations, using alternative samples and using alternative exposure measures to sort banks by arbitrage intensity.

There are two main contributions of this paper to the literature on CIP deviations. First, 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. Second, it complements the current literature by providing evidence that suggests that CIP deviations might not only be an important phenomenon to asset pricing, but it can also affect firms and households through changes in the currency composition of their loans.[6]

The literature on CIP deviations, has broadly addressed three topics. First, it has shown CIP deviations have been common since the financial crisis. Examples of these papers include Baba, Packer, and Nagano (2008); Baba and Packer (2009); Coffey, Hrung, and Sarkar (2009); Mancini-Griffoli and Ranaldo (2011); Du, Tepper, and Verdelhan (2018), where Du, Tepper, and Verdelhan (2018) highlights that this is not just a phenomenon seen during the financial crisis, but has been present after the crisis. Second, the literature has also addressed why these deviations exist. Examples are Du, Tepper, and Verdelhan (2018); Borio, Iqbal, McCauley, McGuire, and Sushko (2018); Rime, Schrimpf, and Syrstad (2020); Wallen (2019)[7]. Finally, another set of papers study the relationship between CIP deviations and other asset prices, such as the dollar (Avdjiev, Du, Koch, and Shin, 2019) and credit spreads of corporate bonds (Liao, 2020).

[6]Papers that have studied CIP deviations outside asset pricing include Ivashina, Scharfstein, and Stein (2015) and Amador, Bianchi, Bocola, and Perri (2020). Ivashina, Scharfstein, and Stein (2015) 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. Amador, Bianchi, Bocola, and Perri (2020) show that central bank's FX policy can be costlier when it conflicts with the zero lower bound and CIP deviations are allowed. A difference with my paper is that in both cases, the effects on the real economy are not directly *due* to arbitraging CIP deviations, but rather the result of shocks and policy 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.

[7]Du, Tepper, and Verdelhan (2018) establish a causal link to balance sheet constraints. Other papers have also added other explanations for CIP deviations: bank credit risk and liquidity (Borio, Iqbal, McCauley, McGuire, and Sushko, 2018), unaccounted real marginal funding costs (Rime, Schrimpf, and Syrstad, 2020) and imperfect competition (Wallen, 2019).

Most of the papers that address CIP deviations describe a setting that pertains to developed economies. Because in most of the sample in this paper there were carry trade inflows in Peru, the setting in this paper resembles that in Keller (2020) and Amador, Bianchi, Bocola, and Perri (2020). In both cases, there are CIP deviations that arise in a setting with capital inflows and a Central Bank that intervenes in the exchange rate to mitigate the FX appreciation.

A secondary contribution of this paper relates to the understanding of internal capital markets in the banking system. This paper shows new empirical evidence on how internal capital markets work for a bank that has to allocate scarce currency-specific liquidity between its lending and its trading division. 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). 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. In this paper I study a different dimension of reallocation, and this is between business divisions.

This paper is organized into five sections. Section 2 reviews the CIP condition. Section 3 describes CIP deviations in Peru and its banking system. Section 4 describes the data. Section 5 is the main section of the paper. It presents the methodology and results. Finally, Section 6 concludes.

2 Review of CIP

This section reviews how CIP works and how arbitraging CIP deviations is done. It also introduces definitions I use later on.

CIP is a non-arbitrage condition. It states that an investor should be indifferent between the following two lending strategies: (i) lend a particular currency directly or (ii) lend it synthetically. These are shown in Figure 1.

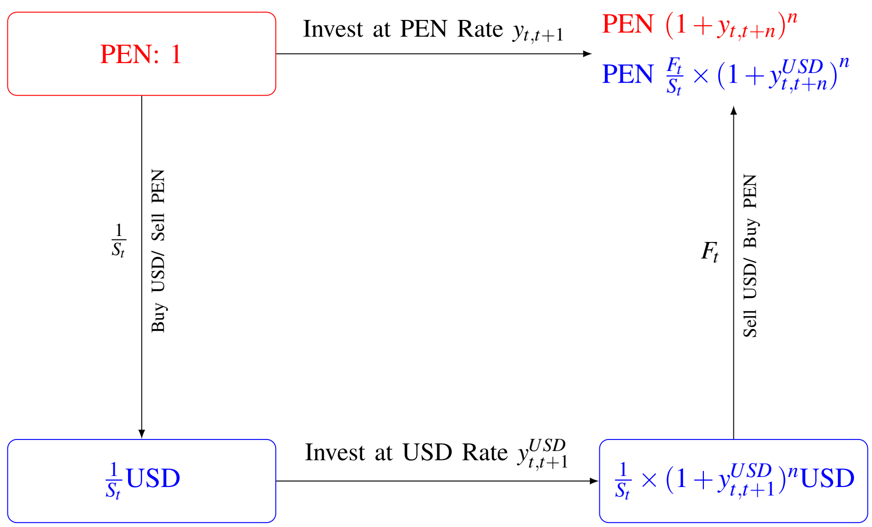

Figure 1: Example of Covered Interest Rate Parity (CIP)

This figure shows an example of CIP. In this example, an investor should be indifferent between two strategies. The first is to lend 1 sol (PEN) directly at the rate $y_{t,t+1}$. When the investor does this, at $t+1$ the investor will have PEN $1+y_{t,t+1}$. This is the red strategy in the figure. The second strategy is highlighted in blue. This second strategy 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 $\frac{1}{S_t} \times (1+y_{t,t+1})$. CIP means that locking, as of time t, 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 dollars) 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 return of the red and blue strategies are the same: $1+y_{t,t+1} = \frac{F_t}{S_t} \times (1+y^{USD}_{t,t+1})$.

The first lending strategy of lending directly is shown in red in Figure 1. As an example, consider the currency is soles (PEN). The n-year annualized rate of return of lending PEN directly is $y_{t,t+n}$ and hence, at time $t+n$ the investor will have PEN $(1+y_{t,t+n})^n$.

The second lending strategy, lending soles synthetically, is shown in blue in Figure 1. This strategy begins with changing the PEN 1 that the investor has at time t to dollars (USD) at an FX of S_t PEN per USD. The investor then lends the $\frac{1}{S_t}$ directly at the n-year annualized USD rate of $y^{\$}_{t,t+n}$. Consequently, in $t+n$, the investor will receive $\frac{1}{S_t} \times (1+y_{t,t+n})^n$ dollars. At time t, the investor also uses forward contracts to lock into a $t+n$ FX and convert the USD loan proceeds into PEN. Denoting the forward FX as $F_{t,t+n}$, the investor converts its USD loan proceeds into PEN $\frac{F_{t,t+n}}{S_t} \times (1+y^{\$}_{t,t+n})^n$. Therefore, under CIP, the return of the red and blue strategies is the same:

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

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) 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 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 the analysis in this paper is from the Peruvian banks' perspective, define the cross-currency basis in soles terms:

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

As shown in Appendix A, the definition of the cross-currency basis in dollar terms ($x_{t,t+n} = y^{\$}_{t,t+n} - y^{\$,fwd}_{t,t+n}$) is equivalent to Equation (3).

When the cross-currency basis is positive (negative), the arbitrageur profits by lending (borrowing) soles synthetically and borrowing (lending) them directly in the money market. The specific transactions that the arbitrageur does consist of: (i) borrowing soles (dollars) directly, (ii) converting these soles (dollars) to dollars (soles), (iii) lending in dollars (soles) while (iv) engaging in a forward contract that sells the dollar (soles) loan proceeds to convert them to soles (dollars). With the soles (dollars) received from the forward contract, the arbitrageur pays the soles (dollars) it borrowed. What remains as profit, in terms of annualized return, is the cross-currency basis (in absolute terms).

Intuitively, the sign of the cross-currency can be interpreted as relative scarcity of a currency. The scarcity of a currency is the currency in which the market in general wants to borrow but not lend. When the cross-currency basis is negative, there is relative abundance of soles compared to dollars. Investors that might not have access to the soles cash rate are willing to lend soles in the soles swap market at a lower rate than the soles cash rate. An analogous interpretation is that the market generally wants to invest in soles but not borrow in soles. Instead, the market prefers to borrow dollars but not lend in dollars. This last statement becomes clear when expressing the 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 that 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 describes the setting. Section 3.1 describes the behavior of CIP in Peru and in other Latin American countries. Section 3.2 describes the Peruvian banking system.

3.1 CIP Deviations in Peru and Other Latin American Countries

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 2005 and 2013.[8] The dotted gray line traces the "Chilean-Mexican basket," which is the average basis for Chilean (USDCLP) and Mexican peso (USDMXN) pairs. The orange line traces the "Latin American basket," which is the average basis for the Brazil real (USDBRL), Chilean peso (USDCLP), Colombian peso (USDCOP) and Mexican peso (USDMXN) against the dollar.

There are three takeaways from this figure. First, both for USDPEN and other emerging markets, CIP deviations have been economically large. In Peru, it has oscillated between -2 and 2%, being many times above 1% in absolute value. Figure 2 shows that the average of the absolute cross-currency basis for the USDPEN and for the Latin American basket has been approximately 0.60% during the sample of this paper. While this basis decreases when accounting for bid-ask spreads, even accounting for these spreads, the average absolute value is 0.23%, which although significantly smaller, it is still large. Moreover, at moments, even after transaction costs, the cross-currency basis in Peru has also been above 1% in absolute value.

[8] I end the sample in February 2013 because after this date there were many regulations on the bank lending and on the forward side that make it difficult to analyze later on the effects of arbitraging CIP deviations on bank lending.

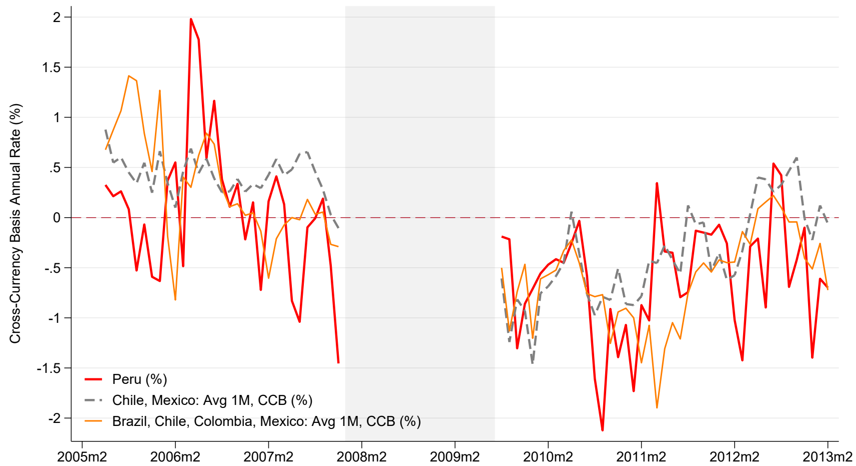

Figure 2: CIP deviations in Peru and other Latin American countries

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. Although the level of Peru's 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 basis are computed using the local currency against the dollar and they are all 1-month basis. The shaded gray area represents the Global Financial Crisis. I am not showing these months because I will not be using this sample to prevent an outlier period from affecting the results and because the significant deviations affect the scale.

Second, the USDPEN cross-currency basis is very correlated to the basis of other Latin American countries. The correlation between USDPEN and the Chilean-Mexican basket is 0.54 and between USDPEN and the Latin American basket is 0.44.

Finally, excluding the financial crisis, most of the sample has negative cross-currency basis. This is both the case in USDPEN and in the other Latin American countries. Hence, on average, the profitable strategy for Peruvian banks has been borrow the local currency synthetically and lend it directly. However, an important difference between the cross-currency basis in these developing economies and those in developed economies is that the cross-currency basis of developing economies has switched signs at different times. This is very rare in developed economies, where, with the exception of the New Zealand dollar and the Australian dollar, the cross-currency basis of developed economies has been negative (see Du, Tepper, and Verdelhan (2018)). Possible explanations for the different dynamics include dollarization and capital controls, which affect the relative scarcity of dollars and soles to which different investors have access. Appendix B discusses possible explanations for the different dynamics between developed and developing economies.

3.2 Peruvian banking system

The financial system in Peru is composed by banks and other types of financial institutions, such as financial corporations, financial cooperatives known as "cajas" and leasing companies. Because banks and other financial institutions have different regulations and because of greater data limitation on financial institutions, I only focus on banks, which concentrate more than 90% of the assets of the financial system. However, the results of this paper are robust to including the whole financial system.

The commercial banking system in Peru is composed by 13 banks. The main business division across Peruvian banks is household and commercial lending, which represents 62% of the banking system's assets. The other important division is trading, which makes investments in securities and money market instruments.

Banks borrow and lend in soles and dollars. Borrowing and lending in local and foreign currency, a phenomenom known as "dollarization" is common across emerging economies.[9] During the sample period, loan and deposit dollarization averaged 59 and 55%, respectively. Firms and households borrowing in dollars are, in its majority, not hedged. Indeed only a small fraction of firms are exporters or have hedging instruments.

In contrast to firms and households, banks need to hedge their FX position. This is common in emerging economies. They have limits on their total FX exposure, which is the sum of the spot and forward position. [10] Banks can have long dollar spot positions as long as they are mostly offset with forward positions.

Offsetting spot positions with forward positions is also what is required to arbitrage CIP deviations. Then, one alternative interpretation of the results is that CIP deviations provide a profitable way to hedge in a particular direction. Banks can exploit this and decide to hedge in the direction which CIP deviations shows it is cheaper or more profitable for them to hedge.

[9]According to the Financial Soundness Indicators database (IMF), economies like 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

[10]Limits on the total FX position is different than the limits on forward holdings studied in Keller (2020)

4 Data

The sample period for all datasets is February 2005 through February 2013. February 2005 is when one of the main datasets, the credit registry, begins. February 2013 is the sample's end date because, from the end of 2013 until at least the start of 2016, there are many confounders. [11]

First, I obtain market-based data on foreign exchange and money market data from Bloomberg. I also use local interbank rates obtained from the Central Bank of Peru, Chile and Mexico. I have used all of these to compute cross-currency basis across various currency pairs. The summary statistics of the USDPEN cross-currency basis and other currency pairs is reported in Table A.I in the Online Appendix.

I use the interbank rates to compute the cross-currency basis as the interbank rate is the key and most liquid money-market instrument that Peruvian banks use for trading. The interbank dollar rate in particular reflects better the cost of funding for Peruvian banks compared to Libor. This is seen in Figure 3. At times when the the cross-currency basis was negative, the dollar interbank rate has been greater than Libor. Therefore, as shown in Figure 3, using the dollar interbank rate yields significantly smaller deviations from cross-currency basis than Libor.[12]

Second, I use bank-level data combined from a series of individual bank reports to the bank regulator, SBS. These reports, mandatory for all banks operating in Peru, are largely 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, which is the net long dollar position of all trades that are currently active (i.e. not expired). More precisely, the net long dollar forward position of a bank at time t is:

[11]These confounders include a deep depreciation shock and various regulations that came with it. Given that the risk aversion associated with the exchange rate also affects fir4ms and households' demand for borrowing dollars and that this is an unobservable variable that varies for each household and firm, it is also difficult to control for the changes in credit demand that could be associated with the exchange rate or expectations of the evolution of the exchange rate as well as the risk premia.

[12]The higher dollar interbank rate compared to Libor is not due to risk aversion. On the contrary, during these periods of times, the credit default swap was at its minimum and there were capital inflows. An explanation for the higher interbank dollar rate seems more linked to the FX intervention of the Central Bank. To mitigate the currency appreciation from inflows, the Central Bank bought dollars in the spot market. These dollars were not sterilized, and therefore, the Central Bank's actions could have decreased the dollar liquidity. Such liquidity could not be easily substituted with dollar borrowing from abroad due to capital controls on inflows discussed in Keller (2020).

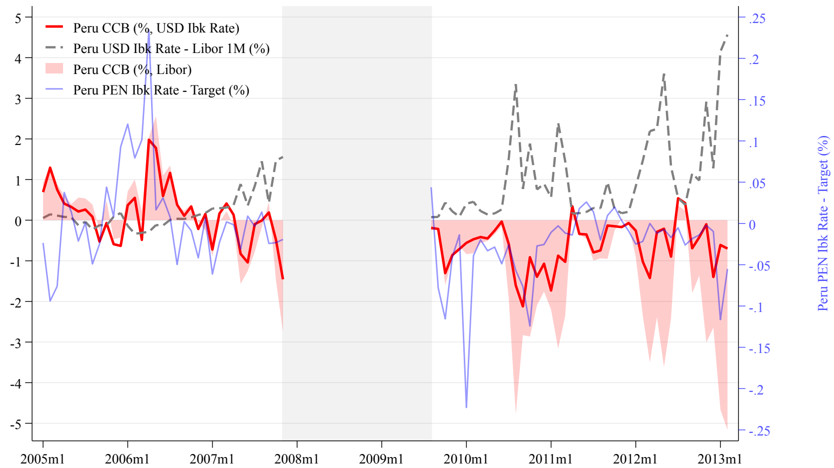

Figure 3: CIP deviations and Interest Rate Spreads

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 1-month Libor. The solid red line is the cross-currency basis computed using dollar interbank rates. The solid red line is the cross-currency basis taken as benchmark for the analysis in this paper. The dollar spread, the gray dotted line, equals the dollar interbank rate in Peru minus 1-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 clearer visualization, the soles interbank spread uses the right axis. The sample period is between February 2005 to February 2013, which are the dates corresponding to the sample of this paper.

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

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 forward that expired. I verify that these positions equal those that are reported as forward positions in other confidential reports sent to the bank regulator.

The second report contains their daily spot transactions. I have corroborated that the daily transactions are consistent with their reported forward and spot positions. More specifically, a bank's long dollar spot position can be computed in two ways:

$$\text{Spot Pos.}_t \equiv \text{Spot Pos.}_{t-1} + \text{USD purchase}_t - \text{USD sale}_t \tag{4}$$

$$\equiv \text{USD Asset}_t - \text{USD Liab}_t \tag{5}$$

where Spot Pos_t is the net long dollar 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 are 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 (4)) equals the one computed by Equation (5).

The third report contains their daily positions on various money market accounts, including interbank loans, financial obligations, investments in short term assets and liquidity ratios. The fourth report includes the interest rates paid on various types of deposits as well as their balances. Finally, I also use monthly public balance sheets.

Panel A of Table A.II in the Online Appendix shows the summary statistics of additional non-balance sheet accounts, such as liquidity, profitability and FX derivatives. Notably, FX 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 do not trade FX forwards or swaps at all, while for others, the volume of these trades represents more than 80% of their assets.[13] This table also presents summary statistics of "net matched position" and $\hat{\beta}$, which are discussed later, 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 long (short) dollar spot that is matched with a net short (long) dollars forward. The $\hat{\beta}$ is the estimated sensitivity of assets allocated to arbitraging CIP deviations following a 1pp increase in the cross-currency basis.

Finally, I also use the credit register collected by the SBS. This constitutes the most granular dataset on bank loans and, jointly with the spot and forward datasets, is the main dataset used in this paper. The 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 dollars) in aggregate with all the financial system.

Almost 28,000 firms are included in the credit register. Table A.II Panel B shows the summary statistics of these firms. Those labeled "small firms" have yearly sales below 20 million soles

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

(approximately 6.5 million dollars). The medium firms have yearly sales between 20 and 200 million soles (6.5 to 65 million dollars) and the large firms have yearly sales above 200 million soles[14].

5 Methodology and Results

This section studies the effect of arbitraging CIP deviations on bank lending. I proceed in three steps. First, in Section 5.1, I show that banks' money market and FX transactions are consistent with arbitraging CIP deviations but that some banks arbitrage more than others. Second, 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. Finally, as a third step in Section 5.3, I provide evidence showing that arbitraging CIP deviations is associated with changes in lending.

5.1 Step 1: Are banks' transactions consistent with arbitraging CIP deviations? Are there differences across banks?

To show that banks' money market and FX transactions are consistent with arbitraging CIP deviations, I show that the correlations between CIP deviations and banks' FX and money market transactions are statistically significant and have the expected signs. I do this both at 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. I do this because, as per Section 2, arbitraging a positive basis requires banks to borrow soles (PEN), whereas it requires dollar (USD) borrowing when negative. Therefore, an arbitrageur is likely to increase soles borrowing when the cross-currency basis is positive, as compared to when the basis is negative. More precisely, I estimate Equations (6a) and (6b), which are aggregate and bank-level estimations respectively:

$$y_t = \theta_0 + \theta_1 \text{CCB}_t \cdot \mathbf{1}(\text{CCB}_t > 0) + \theta_2 \text{CCB}_t \cdot \mathbf{1}(\text{CCB}_t \leq 0) + \varepsilon_t \tag{6a}$$

[14]This corresponds to the "medium", "large" and "corporate" category that the SBS uses to classify firms.

$$y_{bt} = \theta_0 + \theta_1 \mathrm{CCB}_t \cdot \mathbf{1}(\mathrm{CCB}_t > 0) + \theta_2 \mathrm{CCB}_t \cdot \mathbf{1}(\mathrm{CCB}_t \leq 0) + \text{Bank FE} + \varepsilon_{bt} \tag{6b}$$

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 FX positions, scaled by total assets. Money-market positions include interbank borrowing, obligations with financial institutions[15], investing in the Central Bank's certificate of deposits or sovereign debt, investing in other bonds. FX positions include FX 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 are θ_1 and θ_2. They capture the correlations between y_t and the basis when it is positive and when it is negative, respectively.

Table 1, Panel A shows the expected results. These are split into three groups: borrowing, FX and lending. As the cross-currency basis increases, arbitraging banks: (i) increase their borrowing in soles and decrease their borrowing in dollars; (ii) buy more dollars spot and sell dollars forward; (iii) lend more in dollars and less in soles. Asymmetry is also present and in the expected direction, both in terms of magnitude and statistical significance. When the basis is positive, banks borrow more in soles than when it is negative. Banks also buy more dollars spot, sell more dollars forward and invest more in dollars when the basis is positive than when it is negative.

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. For example, when the basis is positive, a 1 pp increase in the cross-currency basis is associated with a 3.34 pp increase in the spot dollar long position, but financial obligations in soles only increase by 1.13 pp and interbank loans by 0.31. This means that banks are only funding approximately 40% of their dollar purchases with new soles borrowed with interbank loans and financial obligations; the analogous occurs with dollar borrowing when the basis decreases. Accordingly, banks will need to fund their dollar purchases as the basis increases through other sources, which can include bank deposits or directly reducing funding in different business divisions (i.e., commercial and personal lending).

[15]This includes from other financial institutions that are not banks, the Central Bank and financial institutions abroad

At this point, a question that arises is who is on the other side of the arbitrage? Although I do not have information on the counterparty for all transactions involved, I do have counterparty information for forward contracts. I find that foreign investors are on the other side of arbitrage transactions. This is not the case for local investors.[16] An explanation for this is market segmentation between foreign and local banks. Because of capital controls and because soles are not deliverable abroad, foreign investors will find more costly and difficult to arbitrage CIP deviations (see Appendix B for details on market segmentation). What they can do instead is engage in carry trade using forward contracts, which is something local banks cannot do because regulation limits their FX exposure.

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

To further analyze differences in banks' ability 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 basis. Then, I use this measure to compute bank-specific sensitives.

Construction of arbitrage proxy. To construct the proxy for the share of a bank's assets invested in arbitraging the basis, I compute a daily measure of the forward and swap position of a bank that is offset by its spot position.[17] The amount of a bank's long forward position that is effectively matched with its short spot positions is the proxy. I call this variable the "matched position" of

[16]This is shown in Table A.III in the Online Appendix. This table shows the estimated correlation between the cross-currency basis and the share of dollars forward local banks buy, splitting the sample between foreign and local investors. When trading with foreign investors, a 1pp increase in the cross-currency basis is associated with a 4pp decrease in local banks' share of dollar purchases from foreign investors. This result is not present in trades with local investors. 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.

[17]I compute positions, that is stock, 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.

a bank. This measure can capture 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 FX positions because they are a cleaner proxy than the bank's use of the money market.[18] Formally, I define the matched position of a bank as follows:

$$\text{Matched}_{bt} = \begin{cases} +\min\{|\text{Spot Pos.}|, |\text{Fwd+Swap Pos.}|\} & \text{, if Fwd+Swap Pos.} > 0 \wedge \text{Spot Pos.} < 0 \\ -\min\{|\text{Spot Pos.}|, |\text{Fwd+Swap Pos.}|\} & \text{, if Fwd+Swap Pos.} < 0 \wedge \text{Spot Pos.} > 0 \\ 0 & \text{, if sgn(Fwd+Swap Pos.)} = \text{sgn(Spot Pos.)} \end{cases} \tag{7}$$

Because the matched position of a bank (Matched_{bt} in Equation (7)) is the amount of a bank's long dollar forward position that is offset with short spot positions, it is computed as the minimum between the absolute value of the spot position and the forward position. Matched_{bt} is positive 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 (7)), and negative when the converse occurs (the second case) [19]. When banks do not offset spot positions with forward positions, they are not arbitraging so Matched_{bt} is zero. Because arbitraging CIP deviations involve selling dollars spot and buying dollars forward when the cross-currency basis is positive, the expected correlation between Matched_{bt} and CIP deviations is negative.

In any case, because banks need to hedge their forward with their spot position, when a bank decides not to renew a forward position, it will also need to change its spot position.

[18]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 performed with other less-traditional assets like lending to the local corporate or household sector. To sum up, 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 FX 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 not coincidence, that both the spot and forward + swap positions of banks had the strongest and most robust correlation with the cross-currency basis in Table 1.

[19]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 performs when it arbitrages CIP and the basis is positive, as arbitrage requires buying dollar spot and selling dollar forward.

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

$$\left(\frac{\text{Matched}}{\text{Assets}}\right)_{bt} = \alpha_b + \beta_b \text{CCB}_t + \varepsilon_{bt} \qquad \forall b \in B \tag{8}$$

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 negative 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 very negatively correlated with the cross-currency basis. During the sample period, the correlation between these two series is -0.70.

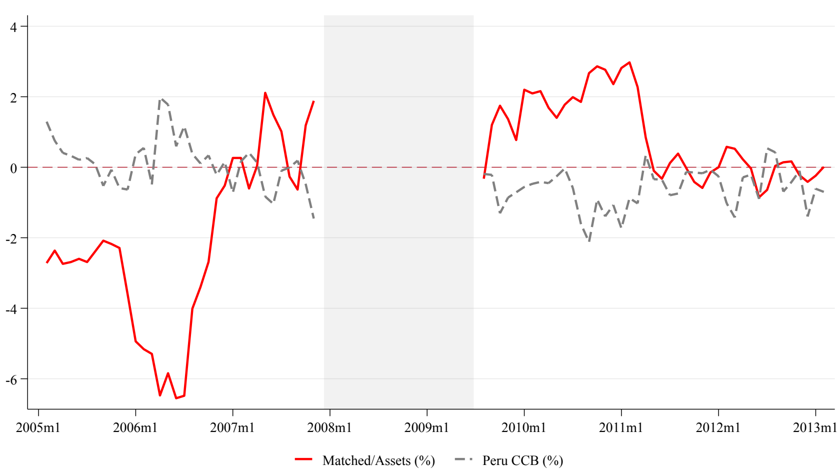

Figure 4: CIP deviations and Matched/Assets

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 between February 2005 to February 2013, which are the dates corresponding to the sample of this paper.

At the bank-level, we should observe that $\beta_1 < \beta_2 < 0$ if bank 1 pursues a more aggressive arbitrage strategy than bank 2, given that bank 1 matches a higher percentage of its assets in the direction predicted by arbitrage when the basis changes by 1 pp. Consequently, I interpret the estimated $\hat{\beta}_b$ coefficient as proxy of bank b's intensity of arbitrage abilities/activities.

Estimating Equation (8) separately for each bank yields considerable heterogeneity in the resulting coefficients. Although I cannot show the regression results for each bank due to confidentiality agreements, Figure 5 shows the smoothed distribution of the coefficients. A concentration of banks is shown 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 [-0.2,0] and [-4.8,-1.6], respectively.

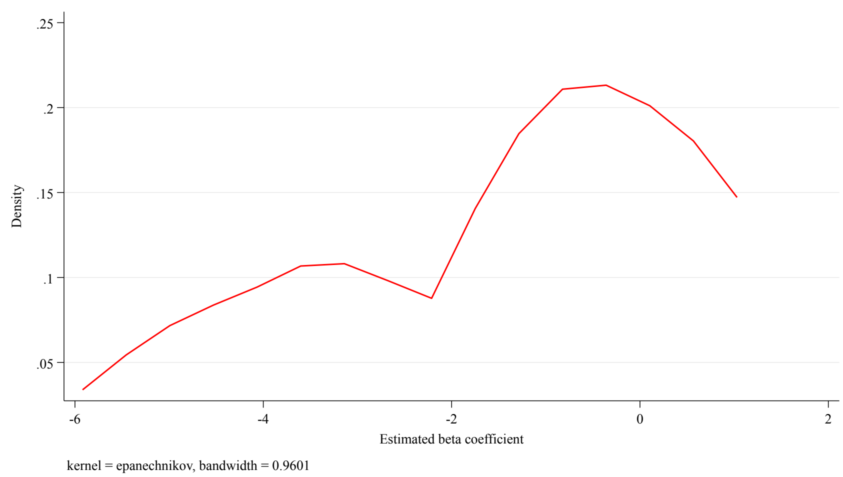

Figure 5: Smoothed density of the estimated $\hat{\beta}$ coefficients

This figure shows the smoothed distribution of the coefficients. It does not show the individual regression results for each bank due to confidentiality agreements.

I verify that $\hat{\beta}$s effectively capture arbitrage ability. The FX and money-market transactions of banks that arbitrage more (have higher absolute value $\hat{\beta}$) are more consistent with arbitraging CIP deviations than those that arbitrage less. This is shown in Table 1 Panel C and Panel D. These panels show the results of splitting banks into high and low-arbitrage banks and estimating the same regressions than 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. More specifically, the coefficients for high-arbitrage banks (Panel C) are, generally, very consistent with banks that are using these accounts for arbitrage, both in terms of sign, significance and asymmetry. However, the coefficients for the low-arbitrage banks (Panel D), are either: (i) opposite to arbitrage; (ii) non-significant; or (iii) smaller than their counterparts from Panel C. These findings provide evidence suggesting that $\hat{\beta}$s are a good measure to proxy for banks' arbitrage activity.

5.2 Step 2: Is the currency needed to arbitrage CIP deviations scarce?

Section 5.1 shows banks' transactions are consistent with arbitraging CIP deviations. This section examines whether the currency that banks need to borrow to arbitrage is scarce at the time that CIP deviations exist. If this is the case, it means that banks are allocating a scarce resource to arbitraging CIP deviations and it can therefore affect funding of that currency in other business divisions, such as their commercial lending division. For example, consider that the cross-currency basis is positive. Arbitraging these deviations requires borrowing soles. Banks can source funds internally or externally. On one hand, if banks choose to source funds internally, they will be reallocating soles resources away from other divisions. If this division is the lending division, soles lending falls. On the other hand, if banks source externally, they need to pay more for soles funding. The result is likely higher soles lending rates that can induce firms to substitute their soles borrowing for dollar borrowing. The converse happens when the cross-currency basis is negative.

A first 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. As shown in Figure 3, the soles interbank rate increases above the Central Bank's target rate when the cross-currency basis is positive and arbitraging CIP deviations require banks to borrow soles. Similarly, the dollar interbank rate increases above Libor when the cross-currency basis is negative and arbitraging CIP deviations require 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 are already computed with interbank soles and dollar rates. Therefore, although these changes in interbank rates close the cross-currency basis gap, the CIP deviations are much larger than the changes in rates.

More formally, I present evidence that banks seem to face borrowing constraints in the currency required to arbitrage by replicating the regressions of the previous section (Equations (6a) and (6b)) using interest rate spreads[20] and liquidity ratios. Table 2 presents the results. In aggregate, a 1pp increase in the cross-currency basis is associated with an increase of 0.3pp in the soles term deposit spread and a decrease in 2.5pp decrease in the share of soles liquid assets[21]. Analogously, a 1pp decrease in the cross-currency basis is associated with an increase between 0.35 and 0.57pp in the dollar spread and an increase of 1.61 to 3.75pp in the share of dollar liquid assets[22].

Although a possible explanation for the scarcity of the currency required to arbitrage could be the demand of funds to arbitrage CIP deviations, it is possible that CIP deviations are not the main driver of these correlations. CIP deviations correlate with other macroeconomic factors (eg., the FX and interventions by the Central Bank in the FX market) and therefore, I do not claim causality. On one hand, estimating bank-level regressions of Table 2 for for 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.[23] On the other hand, the liquidity ratios' coefficients are notably larger and more significant for the high-arbitrage banks, whereas the low-arbitrage banks have non-significant coefficients that are also smaller in absolute value. This finding suggests that banks' arbitrage is driving part of these liquidity changes.

However, importantly, the origin of the scarcity of liquidity 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 and therefore, to

[20]I use are interest rate spreads over the monetary policy target rate so as not to pick up changes in monetary policy. For soles rates, I use 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 Libor yields very 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 as private conversations with trading desks in Peru suggested these are the rates I should use to compute CIP deviations as these are both borrowing and lending rates for banks, I have also done robustness checks using with different rates, such as Libor, risk-free rates computed by van Binsberger, Diamond, and Grotteria (2021). The results are robust to these changes in computation of the cross-currency basis.

[21]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 that can be used for new lending.

[22]Notice that a direct channel that affects the share of liquid assets is arbitraging CIP deviations. Arbitraging CIP deviations must involve buying a particular currency in spot and this 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.

[23]Regressions for the interbank loan spreads are not estimated again at the bank-month level because I do not have the interest rates paid for these loans at the bank level.

arbitrage CIP deviations, they need to reallocate funds internally or pay more to obtain funds externally. Either possibility can impact bank lending and this is what is going to be tested in the next section, Section 5.3.

5.3 Step 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 there seems to be scarcity in the funding currency can affect bank lending in soles and in dollars. Section 5.3.1 presents the methodology and Section 5.3.2 presents the results.

5.3.1 Methodology

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

The main regression specification, shown in Equations (9a) and (9b), addresses these problems in three ways. First, it compares how banks with different abilities to arbitrage CIP deviations 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 abilities to arbitrage CIP deviations change their lending to the same firm on 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 as instrumental variable (IV) the cross-currency basis of Mexico and Chile not only reduces the influence of shocks to the Peruvian economy on the estimation results, but also prevents the results from being biased from Peruvian banks' trading decisions in the FX market that affect the USDPEN cross-currency basis. More precisely, I estimate the following two-stage least squares model:

$$CCB_{t-1}^{\text{Peru}} \times \text{Arb.Intensity}_b = \gamma_0 + \gamma_1 \text{CCB}_{t-1}^{ChMex} \text{Arb.Intensity}_b + X'_{b,t-1}\Theta + \psi_b + \upsilon_{b,t-1} \tag{9a}$$

$$y_{bft} = \alpha_0 + \alpha_1 \, \widehat{CCB_{t-1}^{\text{Peru}} \times \text{Arb.Intensity}_b} + \psi_{bf} + \psi_{ft} + X'_{b,t-1}\Psi + \varepsilon_{bft} \tag{9b}$$

where y is the observed credit outcome (log of USD, PEN, total, share of USD loans) given by bank b to firm f on month t[24]; CCB_{t-1}^{Peru} is the one-month lagged cross-currency basis of USDPEN; CCB_{t-1}^{ChMex} is the average one-month lagged cross-currency basis of Chilean and Mexican peso against the dollar (USDCLP and USDMEX, respectively); -$\hat{\beta}$ is the negative of the bank $\hat{\beta}$ estimated in Section 5.1 and measures the bank arbitrage intensity level[25]; $X_{b,t-1}$ is a vector of one-month lagged bank controls; ψ_b, ψ_{bf} and ψ_{ft} refer to bank fixed effects, bank-firm fixed effects and firm-month fixed effects, respectively. Equations (9a) and (9b) refer to the first and second stage of the two-stage least squares model, respectively.

I use the average between the one-month USDCLP and USDMEX cross-currency basis for two reasons. The first reason is that a condition for the instrument to be valid is that it must be highly correlated with the USDPEN cross-currency basis. The USDCLP and USDMEX basis are

[24] For this regression, I sum across all types of loans for each bank-firm-month. Each observation present 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 prevent from 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 FX 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 FX to have a constant FX. The results remain.

[25] I use the negative value as to have $\hat{\beta}$ in positive numbers and facilitate interpretation. Recall that, as arbitrage predicts, these $\hat{\beta}$s are negative. Then a greater value of $-\hat{\beta}$ is indicative of a bank that arbitrages.

the two Latin American currencies whose correlation with the USDPEN cross-currency basis is the strongest. As shown in Table A.I, the average 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 that I present later that suggest that there is not a weak instrument problem. The second reason is that Peruvian banks barely trade these currencies and are 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.[26]

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' abilities 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 result of this specification is that 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 one percentage point increase in the cross-currency basis when lending to the same firm on the same month. Then $\hat{\alpha}_1$ simultaneously compares (i) the lending of the same bank to the same firm at different levels of CIP deviations and (ii) the lending of high arbitrage-intensive banks relative to less arbitrage-intensive ones.

Although the baseline regression specification addresses various concerns, one could still be worried about the heterogeneity across banks and the correlation between the cross-currency basis and other macroeconomic shocks. To alleviate these concerns, later I also redo the analysis

[26] I compute these numbers from the dataset that includes all forward transactions of banks. Included here are also trades between MXN and CLP against PEN.

narrowing the sample to the most similar banks as well as analyze how changes in the FX, a variable known for comoving with CIP deviations, affects the results.

I perform various other robustness checks after presenting the baseline results. These checks include using alternative specifications, different samples, different computations of the cross-currency basis, and checks on the standard errors.

5.3.2 Results and Robustness

Below I discuss the baseline regression results as well as results from performing additional robustness checks.

Baseline results. The main takeaway from estimating the baseline regression is that an increase in the cross-currency basis increases lending in dollars and reduces it in soles. These results are all significant at 1%. They are also consistent across alternative specifications and economically large. Banks that allocate 1pp more of their assets to arbitraging a 1pp increase in the cross-currency basis increase their dollar lending by 11 to 40% relative to their soles lending. Decomposing this result into soles and dollar borrowing, I find that this result is not only driven by an increase in dollar lending, but also a decrease in soles lending. The range provided depends on the sample. The most conservative result of 11% is when including only firms that were already borrowing in dollars and soles. The largest result derives from including all firms, and this is what I take as benchmark. In net terms, this represents a change in the currency denomination of the loans and a small change in total loans.

Table 3 shows the first-stage results for various specifications, including the baseline specification (Column 3). These results show that 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 baseline specification using four 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 and log of soles loans. The first five columns in both tables correspond to the OLS results, while the last five correspond to the IV results. 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 results, that result from only considering those borrowing in soles and dollars are found in row 5 of Table A.VI in the Online Appendix.

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, by regulation, will need to hedge.[27] Unless the bank borrows and lends in the same currency, the bank will need to hedge by selling dollars forward. As 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 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, goes against finding a result through the mechanism proposed in this paper. Then, as expected, OLS estimates are significantly lower than the IV estimates.

I perform various robustness checks. In sum, the results are widely robust to various alternative specifications and samples, as well as they are robust to controlling for changes in the FX (a shock that correlates with CIP deviations). Below I describe these checks in more length. The tables for all robustness checks are in the Online Appendix.

Robustness check regarding the FX. Avdjiev, Du, Koch, and Shin (2019) document that the value of the dollar is correlated with the cross-currency basis. Peru is no exception. Figure 6 shows that the value of the dollar (i.e. the FX) is correlated with CIP deviations in Peru.[28] The positive correlation between the FX and the cross-currency basis that is seen for the USDPEN means that when soles (PEN) depreciate, the cross-currency basis increases.

This correlation between the FX and the cross-currency basis can confound the effects of arbitraging CIP deviations because, 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

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

[28] Avdjiev, Du, Koch, and Shin (2019) show that in developed economies, the value of the dollar is negatively correlated with the cross-currency basis. However, in emerging economies this correlation is positive. It is out of the scope of this paper to indicate why this is the case. Instead, I take this correlation as given.

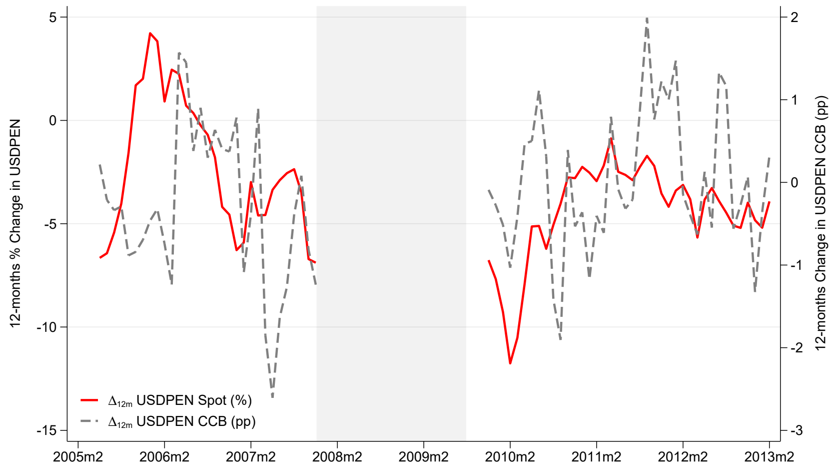

Figure 6: CIP deviations and FX

This plot shows the yearly changes in USDPEN cross-currency basis against the yearly changes in FX. 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 because I will not be using this sample to prevent an outlier period from affecting the results and because the significant deviations affect the scale.

funding and shortage of local currency funding provided to banks. The depreciation of the sol means that households and firms will prefer to switch their savings from soles to dollars. This channel, which I refer to as the FX channel, means that as the local currency depreciates, we can expect banks to increase dollar lending and decrease sol lending to mirror what is happening on their funding side. Although the net effect on bank lending is uncertain as households and firms will probably demand more soles borrowing as the soles depreciates, if the bank supply side dominates, the baseline results could potentially be picking up the correlation with the FX rather than arbitraging CIP deviations.

However, for the FX channel to be a threat to the results, it is not sufficient that it is correlated with the cross-currency basis. The FX channel must also be correlated with banks' abilities to arbitrage. More specifically, to invalidate the results, because the estimation relies on comparing bank lending across banks with different ability to arbitrage, we also need that the FX channel affects more those banks with higher ability to arbitrage. This is still possible, particularly because $\hat{\beta}$, the ability to arbitrage computed in Section 5.1, has not been derived from exogenous or predetermined bank characteristics.

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

$$\left(\frac{\text{Deposits}}{\text{Assets}}\right)_{bt} = \alpha_b^0 + \alpha_b^1 \log(\text{FX})_t + \varepsilon_{bt} \qquad \forall b \in B \tag{10}$$

where the numerator of the dependent variable is either deposits in soles, dollars or total deposits.

I find that the deposit sensitivity to the FX does not affect the most to banks that arbitrage the most. Table A.IV shows the summary statistics of the estimated coefficients, splitting banks into three groups, depending on their arbitrage intensity.[29] The banks in the high range of arbitrage intensity are those for which dollar deposits increase the least when the sol depreciates. In terms of dollars, those with lowest arbitrage intensity are those that show the greatest reduction in sol deposits as the sol depreciates. Therefore, the greater reduction in sol bank lending in banks that arbitrage more after an increase in the cross-currency basis cannot derive from the FX channel. If something, the FX channel for the results in soles works against finding a result. Similarly, it is unlikely that the results for dollar lending are coming from the FX channel as the banks that arbitrage the most are not those with the greatest increase in dollar deposits as the basis increases and the FX depreciates.

Moreover, Table A.V shows that the baseline results are robust to adding the interaction between arbitrage intensity (-β) and log(FX).

Robustness checks on 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 ability 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 could be affecting

[29] All banks have been sorted into the three groups. I show discontinuous ranges $-\hat{\beta}$ in Table A.IV to show that there are discontinuous jumps in the accumulation of banks that allow me to sort banks into the three groups shown in the table.

much 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 more homogeneous. In this sample, the results get stronger.[30] Second, alternative specifications that exclude all time-varying bank controls -including measures of soles and dollar deposits, total assets, profitability and liquidity- yields very similar results to the baseline model. Moreover, adding bank fixed effects even strengthens the results. These results are shown in Table A.VII, which include dropping bank controls and adding fixed effects one-by-one. In general, Table A.VII 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.

Robustness check on firms with foreign trade. An alternative channel through which the correlation the cross-currency basis and the FX can affect the results is through through the effect that the FX has on foreign trade. Exporters could face greater demand as the sol depreciates. Therefore, these firms could 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 more 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.[31] The baseline results are robust to excluding firms with foreign trade. Row 3 of Table A.VI shows the results.

Robustness check on type of loan. A concern is that credit demand for a particular type of loan can be making some firms 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, which are commercial loans.[32] These constitute 50% of the loans given to firms in Peru. As row 4 of Table A.VI shows, 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%. This indicates that

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

[31] 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.

[32] These exclude foreign trade loans, leasing, real estate, credit cards, overdraft, among other.

the baseline results are not driven by particular demands for specific types of loans or bank specialization in this.

Robustness using different calculations for CIP deviations. To verify that the results are not driven by FX and interest rates taken to compute CIP deviations, I provide robustness checks using alternative computations of CIP deviations. First, as shown in Table A.VIII, the results are robust to using CIP deviations that account for bid-ask spreads.[33] Second, because a concern can be that the interbank interest rates might not be capturing well the funding costs of banks, I compute the cross-currency basis taking as alternative the Libor and the inferred put-call parity relationship rates from van Binsberger et al. (2021).

Robustness check using alternative arbitrage intensities. A first 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 robustness check, I estimate $\hat{\beta}$ in (8) but instrumenting the USDPEN basis with that of the average between USDCLP and USDMXN. The results, which are shown in the second row of Table A.IX. The results are robust to the change in the estimation of $\hat{\beta}$. Similarly, Table A.IX shows that the results are robust to a variety of changes in the regressors used, which include not using $\hat{\beta}$ to sort banks, but compare the banks that arbitrage the most with those that either do not arbitrage or arbitrage significantly less, using the arbitrage position as regressor (matched/Assets), as well as just using the USDPEN basis. Because month fixed effects cannot be added when using only the USDPEN basis as regressor, this last specification only uses bank-firm fixed effects and lagged bank controls.

[33] 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 US dollars a the ask rate; ii) sell dollars at the bid spot rate; iii) invest soles at the bid rate; iv) buy dollars forward at the ask forward rate. Therefore, when the cross-currency basis is negative, I compute the basis taking spot bid price and forward ask price. When the cross-currency basis is positive, I use the spot ask price and 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 9bps. Therefore, the dollar bid/ask rate is the mid-market rate minus/plus 4.5 bps.

Robustness check on 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 the majority of countries in the rest of the world, is composed by few banks. Hence, clustering at the bank-level can yield inconsistent standard errors with so few clusters. Because of this, the regressions reported use firm and month clusters. To confirm that the significance of the results is not driven by the choice of clustering, Table A.X 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 bank 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 a currency for another rather than just decreasing the total quantity lent.

I test this proposed mechanism in three steps. First, I investigate whether banks' transactions indicate that they are arbitraging CIP deviations. I show this to be the case but I find that not all banks have the same ability to arbitrage these deviations. Second, I investigate whether banks can easily expand their balance sheets to fund their arbitrage transactions. I find evidence indicating that banks experience difficulties in increasing borrowing to fund their arbitrage transactions. Third and finally, I investigate whether arbitraging CIP deviations can affect bank lending. To do this, I use the finding of the first step, namely, that banks have different abilities to arbitrage CIP deviations, and show evidence suggesting that banks arbitraging CIP deviations shift the currency composition of their lending to firms. In particular, banks that use more of their assets to arbitrage

CIP deviations, decrease their lending in soles relative to dollars after an increase in the USDPEN cross-currency basis.

To the best of my knowledge, this is the first study to suggest that arbitraging CIP deviations can affect bank lending. Given the importance of bank lending on real outcomes, the results in this paper suggest that arbitraging CIP deviations could also have real effects.

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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 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 financial crisis). All USD accounts were transformed into PEN with 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 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 (%)	0.31*	-0.03	1.13**	-1.40*	3.34***	-2.87***	-2.29**	0.16	-0.98	1.17***
	(1.79)	(-1.33)	(2.42)	(-1.87)	(3.43)	(-3.71)	(-2.03)	(1.11)	(-1.00)	(3.38)
OLS: Negative CCB (%)	0.07	-0.06*	-0.25	-2.77***	2.69***	-2.09***	0.61	0.31**	0.57	0.76***
	(1.40)	(-1.81)	(-1.49)	(-4.84)	(5.49)	(-5.01)	(0.56)	(2.53)	(0.48)	(3.42)
Observations	77	77	77	77	77	77	77	77	77	77
Panel B: Bank-level Regressions										
OLS: Positive CCB (%)	0.25	-0.04	0.56*	-0.60**	2.87***	-2.09***	-1.64**	0.28*	-0.84	0.84**
	(1.46)	(-0.84)	(1.78)	(-2.46)	(3.96)	(-3.92)	(-2.58)	(1.99)	(-1.31)	(2.49)
OLS: Negative CCB (%)	0.10*	-0.07	-0.30**	-0.68***	2.17***	-1.80***	0.10	0.28***	-0.13	0.54***
	(1.96)	(-0.97)	(-2.31)	(-2.95)	(4.68)	(-4.40)	(0.11)	(3.44)	(-0.13)	(3.34)
Observations	873	873	873	873	873	873	832	758	873	873
Panel C: High-arbitrage banks										
OLS: Positive CCB (%)	0.51**	-0.04	1.03**	-1.34**	4.54***	-3.65***	-2.27**	0.02	-1.19	0.69**
	(2.07)	(-0.42)	(2.32)	(-2.37)	(4.11)	(-3.97)	(-2.38)	(0.10)	(-1.33)	(2.05)
OLS: Negative CCB (%)	0.18**	-0.12	-0.19	-1.85***	3.66***	-3.23***	0.01	0.32**	-0.32	0.59***
	(2.14)	(-0.94)	(-1.48)	(-4.49)	(4.81)	(-4.54)	(0.01)	(2.34)	(-0.24)	(3.32)
Observations	479	479	479	479	479	479	476	454	479	479
Panel D: Low-arbitrage banks										
OLS: Positive CCB (%)	-0.07	-0.03	-0.01	0.31	0.80***	-0.17***	-0.85**	0.62***	-0.40	1.03***
	(-0.78)	(-1.64)	(-0.03)	(0.75)	(3.10)	(-2.89)	(-2.47)	(4.58)	(-1.08)	(2.79)
OLS: Negative CCB (%)	0.00	-0.00	-0.44**	0.73**	0.36**	-0.05	0.23	0.23***	0.11	0.47***
	(0.03)	(-0.24)	(-2.01)	(2.63)	(2.33)	(-0.62)	(0.34)	(3.63)	(0.15)	(2.73)
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 fonts. Variables are written as percentage of assets (in the 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. Finally, 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 financial crisis). All USD accounts were transformed into PEN with constant FX of February 2005. In all panels, HAC standard errors were used, allowing for 3-month autocorrelation. In adddition, 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 (%)	0.29**	-0.35**	0.04	-0.40**	-2.57**	3.75***
	(2.47)	(-2.29)	(1.17)	(-2.21)	(-2.16)	(4.66)
OLS: Negative CCB (%)	0.26***	-0.57***	0.02**	-0.64***	-2.15***	1.61***
	(3.21)	(-4.01)	(2.10)	(-3.37)	(-3.77)	(3.30)
Observations	77	77	77	77	77	77
Panel B: Bank-level Regressions						
OLS: Positive CCB (%)	0.29*	-0.64***			-2.08***	2.49***
	(1.94)	(-2.92)			(-2.83)	(6.06)
OLS: Negative CCB (%)	0.28**	-0.52***			-2.03***	0.52
	(2.39)	(-3.82)			(-3.71)	(1.30)
Observations	872	873			873	873
Panel C: High-arbitrage banks						
OLS: Positive CCB (%)	0.31**	-0.54***			-3.05***	3.51***
	(2.58)	(-3.02)			(-2.91)	(6.39)
OLS: Negative CCB (%)	0.23***	-0.51***			-3.01***	0.72
	(2.70)	(-3.82)			(-3.77)	(1.15)
Observations	478	479			479	479
Panel D: Low-arbitrage banks						
OLS: Positive CCB (%)	0.27	-0.75***			-0.88	1.23***
	(1.37)	(-2.71)			(-1.59)	(2.72)
OLS: Negative CCB (%)	0.33**	-0.52***			-0.84*	0.28
	(2.07)	(-3.14)			(-1.86)	(1.48)
Observations	394	394			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 (9a). 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 in 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 9a). The F-statistic is the F-statistic of the first stage, given by Kleibergen-Paap rk Wald F statistic. T-statistics are in parenthesis. 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 but excludes the financial crisis.

	(1)	(2)	(3)
$\mathrm{CCB}_{t-1}^{\mathrm{Chile,Mex}} * (-\hat{\beta})$	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 9b. The first four columns show the OLS estimates while the last four show the IV estimates. The dependent variables in logarithm have been multiplied by 100. The ratio of dollar to total loans is expressed in 0-100 scale. T-statistics are in parenthesis. 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 but excludes the financial crisis. 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)

	OLS					IV				
	Log(PEN)	Log(USD)	Log(Total)	Ratio	Log(USD)-Log(PEN)	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***	-24.30***	16.29***	3.377**	1.422***	40.58***
	(-3.48)	(3.05)	(0.89)	(3.35)	(3.82)	(-3.44)	(3.50)	(2.18)	(3.40)	(3.74)
Firm * Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank * Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Cluster	18,374	18,374	18,374	18,374	18,374	18,374	18,374	18,374	18,374	18,374
Month Cluster	77	77	77	77	77	77	77	77	77	77
Observations	1,348,040	1,348,040	1,348,040	1,348,040	1,348,040	1,348,040	1,348,040	1,348,040	1,348,040	1,348,040
Adjusted R2	0.74	0.81	0.72	0.81	0.82	-0.00	-0.00	0.00	-0.00	-0.00

ONLINE APPENDIX

Table A.I: 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 financial crisis. 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 cross-currency basis 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 is the one that has greatest correlation with USDPEN. Within each group, the first row, CCB, corresponds to the cross-currency basis, expressed in percentages (on a scale from 0-100). The following two lines describe the summary statistics narrowing the sample to periods when the basis was either positive or negative. The fourth line shows the absolute value of the CCB. The fifth line shows the 1-month change in CCB in percentage points (pp). This has not been annualized. The sixth row is analogous but using the absolute value of CCB. Finally, the last row shows the year-over-year changes in the FX of that currency pair. The last column of this table shows correlations. In the row corresponding to CCB of either Av.Latam or Av.Chile and Mexico, it shows the correlation between the CCB of Latam or Chile and Mexico wih the CCB of Peru. In the row corresponding to the FX, it shows the correlation between the 1-year FX changes and the 1-year changes CCB on the corresponding countries.

	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.II: Bank-Level, Firm-Level, Bank-Firm Level Summary Statistics

This table shows the summary statistics aggregated at the bank-level, firm-level and bank-firm level. $\hat{\beta}$ is the bank level coefficient estimated from Equation 8 in Part 5.1 from Section 5. "Net Matched Position" refers to the forward and swap position of a bank that is matched with the reverse transaction in its spot position. This variable is used starting from Section 5, Part 5.2.

	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 (EOY, %)	1.93	1.80	1.63	-0.17	5.11	70
FX Derivatives and $-\hat{\beta}$						
$-\hat{\beta}^{CIP}$	1.83	1.77	1.90	-0.00	4.96	13
FX Derivatives/ Assets (%)	19.38	9.56	29.95	0.00	83.57	873
Net Matched Position (Million USD)	6.14	0.00	139.66	-220.28	219.94	873
|Net Matched Position| (Million USD)	74.19	12.37	118.45	0.00	324.43	873
Net Matched Position / Assets (%)	0.93	0.00	4.72	-4.80	10.35	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	5.2	77
Share of Medium Firms (%)	18.4	14.8	6.6	10.1	28.3	77
Share of Small Firms (%)	78.6	83.0	7.9	66.5	88.3	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)	374.18	11.71	3,342.42	0.00	865.28	767,706
USD Credit (Th. USD, Cons FX)	977.43	121.45	6,161.48	0.00	3,142.91	767,706
Total Credit (Th. USD, Cons FX)	1,351.61	193.24	7,356.07	9.55	4,494.72	767,706
Number of bank relationships	2.15	2.00	1.28	1.00	5.00	767,706
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)	450.25	45.98	3,017.53	0.00	1,517.32	1,666,605
Total Credit (Th. USD, Cons FX)	622.61	91.47	3,508.79	0.99	2,156.79	1,666,605

Table A.III: Evidence consistent with foreign investors being on the other side of the arbitrage

To check 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. To do this, I use the dataset that has all of the forward trades done by local banks. I split the forward trades by residency of the counterparty: (i) foreign investors (non-residents or NR in the table below) and (ii) local investors (residents or R in the table below). 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:

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

where y_t is either the fraction of trades where the local bank buys dollars forward (columns 1 and 3 in the table) 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 while columns 3 and 4 show the results for trades done with non-residents. The regression is on a daily frequency, between February 2005 to 2013, excluding the financial crisis.

	(1)	(2)	(3)	(4)
	%NumberTrades	%NotionalTrades	%NumberTrades	%NotionalTrades
Peru CCB (%)	-4.278***	-3.993***	1.008	0.278
	(-5.09)	(-4.56)	(1.86)	(0.65)
Observations	736	736	859	859
Residency	NR	NR	R	R
Adjusted R2	0.0324	0.0247	0.00494	-0.000823

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

Table A.IV: Sensitivity of FX and Arbitrage Intensity

This table shows the summary statistics of the sensitivity of bank deposits to a 1% depreciation split by arbitrage intensity. The arbitrage intensity is measured by -β and estimated using Equation 8. The sensitivity of bank deposits to changes in FX has been estimated using Equation 10.

	Low -$\hat{\beta}$ $0 \leq -\hat{\beta} < 0.2$		Medium -$\hat{\beta}$ $1.6 \leq -\hat{\beta} < 2.6$		Large -$\hat{\beta}$ $3.5 < -\hat{\beta}$	
	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)	0.37	0.18	0.49	0.07	0.26	0.84
Δ Total Dep/Assets to 1% deprec. (pp)	-0.47	0.56	0.49	0.16	-0.27	1.04

Table A.V: 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 the arbitrage intensity (-$\hat{\beta}$). All specifications, unless explicitly noted, use the same fixed effects (firm-month and bank-month fixed effects) and controls (lagged bank controls) as those used in the baseline specification. The first row shows the baseline coefficients. The dependent variables in logarithm have been multiplied by 100. The ratio of dollar to total loans is expressed in 0-100 scale. T-statistics are in parenthesis. 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 but excludes the financial crisis. 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).

	Log(PEN)	Log(USD)	Log(Total)	Ratio	Log(USD)-Log(PEN)
$\text{CCB}^{\text{Peru}}_{t-1} * (-\hat{\beta})$	-16.95***	15.58***	5.110***	1.065***	32.53***
	(-2.88)	(3.27)	(3.05)	(2.96)	(3.32)
$\log(\text{FX})_{t-1} * (-\hat{\beta})$	-1.848***	0.369	-0.138	0.0913***	2.217***
	(-5.03)	(1.23)	(-1.23)	(4.10)	(3.75)
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	17,113	17,113	17,113	17,113	17,113
Month Cluster	75	75	75	75	75
Observations	1,241,908	1,241,908	1,241,908	1,241,908	1,241,908
Adjusted R2	0.00	-0.00	0.00	0.00	-0.00

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

This table shows robustness checks under different samples. All specifications, unless explicitly noted, use the same fixed effects (firm-month and bank-month fixed effects) and controls (lagged bank controls) as those used in the baseline specification. The dependent variables in logarithm have been multiplied by 100. The ratio of dollar to total loans is expressed in 0-100 scale. The first row shows the baseline coefficients. The first five columns show the second stage IV coefficients of the baseline specification (i.e. with lagged bank controls, bank-firm 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). The first row shows the baseline second-stage regression shown in Table 4. The second row restricts the sample to the largest four banks. The third sample restricts the sample to those firms without foreign trade. The fourth row restricts the sample to to commercial loans only. To do so, I started with the loan-level dataset instead of the dataset that aggregated loans at the bank-firm-month level. The dataset aggregated at the bank-firm-month level was used for the other regressions. Finally, the last line shows the coefficients for all the financial system. All the previous regressions were only for banks. Other financial institutions include financials and cajas. These are subject to different banking regulation than banks. T-statistics are in parenthesis. 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 but excludes the financial crisis. 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).

	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	-28.11***	20.03***	-0.24	2.05***	48.13***	669,351.00	12,415.00	77.00
	(-3.27)	(2.88)	(-0.14)	(3.29)	(3.27)			
(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)			

Table A.VII: 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). The first row shows 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 lines below the baseline either drop the bank controls and change the fixed effects specifications. The second row has no controls but has bank-firm and firm-month fixed effects. The third row has no controls and no fixed effects. The fourth row has no bank controls and only bank fixed effects. The fifth row has no bank controls and only firm and bank fixed effects. Finally, the last row has no controls and firm, bank and month fixed effects.

The dependent variables in logarithm have been multiplied by 100. The ratio of dollar to total loans is expressed in 0-100 scale. T-statistics are in parenthesis. 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 but excludes the financial crisis. 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).

	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.VIII: 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 explicitly noted, use the same fixed effects (firm-month and bank-month fixed effects) and controls (lagged bank controls) as those used in the baseline specification. The first row shows the baseline coefficients. The second row shows the coefficients when computing CIP deviations using bid-ask spreads for all of these prices, both for the USDPEN basis as well as the USDCLP and USDMXN basis used as IV. The third row computes the cross-currency basis using dollar Libor rates instead of the dollar interbank rate. Finally, the last row computes the cross-currency using the inferred put-call parity relationship rates from van Binsberger, Diamond, and Grotteria (2021). The dependent variables in logarithm have been multiplied by 100. The ratio of dollar to total loans is expressed in 0-100 scale. T-statistics are in in parenthesis. 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 but excludes the financial crisis. 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).

	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)			

Table A.IX: 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 explicitly noted, use the same fixed effects (firm-month and bank-month fixed effects) and controls (lagged bank controls) as those used in the baseline specification.The dependent variables in logarithm have been multiplied by 100. The ratio of dollar to total loans is expressed in 0-100 scale.
The first row shows the baseline coefficients. The baseline regression is shown in the first row. The second row replaces $-\hat{\beta}$ estimated by Equation (7) 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. The third row replaces $-\hat{\beta}$ in the baseline regression with a dummy that takes the value of 1 for banks that arbitrage the most. These are banks with $-\hat{\beta}$ ¿ 3.5. This threshold has been chosen because there is a significant gap between these set of banks and the next group of banks, which have a $-\hat{\beta}$ of less than 2.6. The fourth row does not use any measure to compare arbitrage intensities across banks and just uses 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 just use firm-bank fixed effects. Finally, the last specification only uses the 1-month lag of negative of "Matched/Assets" as regressor.
T-statistics are in in parenthesis. 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 but excludes the financial crisis. 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).

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: $\text{CCB}_{t-1}^{\text{Peru}} * \mathbf{1}(\text{High Arb Bank})$	-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)			
(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: - 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.X: Standard Errors Robustness Check: Using Different Clusters

This table checks the validity of the standard errors in the baseline regression specification. The first row shows the baseline coefficients of the second-stage regression. The rows after "standard errors" 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 shown in the literature, which is defined in dollar terms, is the same as the definition I use in this paper, which is in soles terms.

Typically the definition used in the literature is:

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

This definition is equivalent the one used in this paper (given by 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:

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

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

B Possible explanations for the differences in the cross-currency basis of developed and developing economies

Explanations for the differences between developed and developing economies possibly stem from differences in the degree of market segmentation in the transactions required to arbitrage and the sources of dollar liquidity.

Market segmentation. The degree of market segmentation in FX and money markets differs between developed and developing economies. Two important factors affect market segmentation in developing economies: (i) capital controls and (ii) delivery of local currency.

Between 2010-2012, various developing countries set capital controls on inflows to limit carry trade inflows. These controls typically involve a series of regulations that affect money markets as well as the forward markets. In the money market, regulations have included high reserve requirements when local banks borrow dollars short-term from abroad, as well as fees when foreign investors would buy short-term local currency debt. In the forward market, regulations have included restrictions for local banks when purchasing dollars from abroad.

In Peru, capital controls on inflows were imposed starting in 2008 and then reinforced in 2011 (see Keller (2020) for a detailed analysis of these controls). A first set of regulation imposed in 2008 included high reserve requirements when local banks borrowed dollars from abroad, as well as high fees for foreign investors when purchasing soles certificates of deposit from the Central Bank. A second set of regulation imposed in 2011 set limits on forward holdings of local banks. These restrictions segment money markets and FX markets between foreign investors and local banks that can partially explain part of the cross-currency basis in Peru and other emerging economies with similar regulations.

Besides capital controls, the delivery of local currency is also an aspect that naturally segments foreign investors from local banks. Typically, emerging market currencies cannot be delivered abroad. This means that for foreign banks to trade FX spot, which is deliverable, they typically need a current account in the emerging economy. This means that foreign investors trade mostly non-delivery forward contracts. This is the case in Peru where, 85% of trades in my sample are non-delivery forwards (NDF).[34] Therefore, large changes in foreigners' demand for dollars in the forward market could create an additional pressure in the forward market. In contrast to this, local banks trade both in the forward and in the spot market and therefore have an advantage when arbitraging CIP deviations.

More generally, there are other factors that affect market segmentation that are present in developed and developing economies. In both cases, local banks usually have an advantage when borrowing and investing in the local currency because they are the authorized agents to participate in auctions from the central bank.

Sources of dollar liquidity. Because of past instability and hyperinflation, various emerging economies are partially dollarized. This means that there is already dollar liquidity in the country. Factors affecting such liquidity included FX interventions from the Peruvian Central bank. Clearly, these factors are not present in developed economies.

[34] This means that only the net profit is exchanged at the end of the forward contract and this is settled in dollars. Indeed, confidential daily FX spot data that banks report to the Central Bank, shows that foreign investors do not trade spot FX. Forward transactions of banks, however, show that 90% of foreign investors' forward trades are NDF.