Arbitraging Covered Interest Rate Parity Deviations and Bank Lending

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In this paper, I propose and test a new channel that can affect bank lending in an emerging markets setting. This channel works as follows. When there are covered interest rate parity (CIP) deviations, banks attempt to arbitrage them. This requires banks to borrow in a particular currency. In the presence of borrowing frictions, banks either increase the rates paid for deposits to arbitrage or shift a portion of the resources used to lend to fund their arbitrage activities. Either case, 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. I show that banks that have greater ability to arbitrage reduce their lending in the currency they need to fund their CIP arbitrage. This is partly compensated by lending in a different currency. This evidence suggests that arbitraging CIP deviations can affect the currency composition of bank lending.

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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. In this paper, I show these deviations also exist in emerging economies and that they 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 an emerging market setting. 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 opportunity to lend 1-month at the risk-free rate in dollars or in soles, the Peruvian currency.

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

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. 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 funded to arbitrage CIP deviations. Yet, we already know 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, 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 reduce lending in soles by 26% and increase their dollar lending by 18% after a 1pp increase in the USDPEN cross-currency basis instrument. 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 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 two steps to mitigate this problem. The first 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.

The second step I take is to focus on a known correlation with CIP deviations that can affect the results on bank lending. This is the role of the FX (Avdjiev, Du, Koch, and Shin, 2019). 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.

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.[2]

[2]Papers that have studied CIP deviations outside asset pricing include Ivashina et al. (2015) and Amador et al. (2020). Ivashina et al. (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 et al. (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.

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)[3]. 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).

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, 2010) 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.

[3] 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).

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.

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, $x_{t,t+n}$. Following conventional definitions from the literature, I define the cross-currency basis as: [4]

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

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).

3 Setting

In this section I describe the setting. I start describing how CIP actually behaves in Peru and how it compares with other Latin American countries. I do this in Section 3.1. Then, in Section 3.2, I describe the Peruvian banking system.

3.1 CIP Deviations in Peru and Other Latin American Countries

Figure 2 Panel A 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.[5] 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.

[4]Typically in the literature, the cross currency basis is defined in dollar terms: $x_{t,t+n} = y^{\$}_{t,t+n} - y^{\$,fwd}_{t,t+n}$ As shown in Appendix A, this definition is equivalent to Equation (3).

[5]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. Appendix B explains the confounders.

Panel B only plots the "Chilean-Mexican basket" juxtaposed with the USDPEN cross-currency basis.

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. Table 1 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. 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 0.51 and between USDPEN and the Latin American basket is 0.38. 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.

3.2 Peruvian banking 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 (represents 34% of assets). This is shown in Table 2, which reports summary statistics of the main sources of funding and lending for Peru's banking system.

Banks borrow and lend in soles and dollars. This is also shown in Table 2. Borrowing and lending in local and foreign currency, a phenomenom known as "dollarization" is common across emerging economies.[6] 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.

[6]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

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.[7] Then, a bank can have a large dollar spot position as long as this is 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.

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 that are discussed in Appendix B.[8]

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 1.

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. The second report contains their daily spot transactions. I have corroborated that the daily transactions are consistent with their reported forward and spot positions. The third report contains their daily positions on various

[7] Limits on the total FX position is different than the limits on forward holdings studied in Keller (2019)

[8] 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 firms 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.

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.

As discussed in Section 3.2, the summary statistics of banks' balance sheets and additional money market accounts are shown in Table 2. Panel A of Table 3 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.[9] This table also presents summary statistics of "net matched position" and $\hat{\beta}$. "Net matched position" is the spot position that has been matched with the opposite transaction in the forward market. The $\hat{\beta}$ is the estimated sensitivity of assets allocated to arbitraging CIP deviations following a 1pp increase in the cross-currency basis. "Net matched position" and the estimation of $\hat{\beta}$ are described in Section 5.1.

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 3 Panel B shows the summary statistics of these firms. Those labeled "small firms" have yearly sales below 20 million soles (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[10].

[9] Interestingly, the three banks that arbitrage the most are not the banks that were most affected by capital controls studied in Keller (2019).

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

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 (4a) and (4b), which are aggregate and bank-level estimations respectively:

$$y_t = \theta_0 + \theta_1 \mathrm{CCB}_t \cdot \mathbf{1}(\mathrm{CCB}_t > 0) + \theta_2 \mathrm{CCB}_t \cdot \mathbf{1}(\mathrm{CCB}_t \leq 0) + \varepsilon_t \tag{4a}$$

$$y_{bt} = \theta_0 + \theta_1 \mathrm{CCB}_t \cdot \mathbf{1}(\mathrm{CCB}_t > 0) + \theta_2 \mathrm{CCB}_t \cdot \mathbf{1}(\mathrm{CCB}_t \leq 0) + \text{Bank FE} + \varepsilon_{bt} \tag{4b}$$

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 transactions, scaled by total assets. Money-market transactions include interbank borrowing, obligations with financial institutions[11],

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

investing in the Central Bank's certificate of deposits or sovereign debt, investing in other bonds. FX transactions 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 5, 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 5, 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 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).

Shifting to the bank-level results, Panel B of Table 5 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. 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 a bank. This measure can capture arbitrage transactions because any CIP arbitrage transaction requires banks to offset their forward transactions with spot transactions. Although banks borrow and lend as part of arbitraging CIP deviations, I rely only on the FX transactions because this is a cleaner proxy than the bank's use of the money market.[12] Formally, I define the matched position of a bank as follows:

$$\text{Matched}_{bt} = \begin{cases} +\min\{|\text{Spot Pos.}|, |\text{Fwd+Swap Pos.}|\} & \text{, if Fwd+Swap Pos.} > 0 \wedge \text{Spot Pos.} < 0 \\ -\min\{|\text{Spot Pos.}|, |\text{Fwd+Swap Pos.}|\} & \text{, if Fwd+Swap Pos.} < 0 \wedge \text{Spot Pos.} > 0 \\ 0 & \text{, if sgn(Fwd+Swap Pos.)} = \text{sgn(Spot Pos.)} \end{cases} \tag{5}$$

Because the matched position of a bank (Matched_{bt} in Equation (5)) 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 (5)), and negative when the converse occurs (the second case) [13]. When banks do not offset spot positions with forward positions, they are not arbitraging so Matched_{bt} is

[12] 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 5.

[13] 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

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.

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:

$$\left(\frac{\text{Matched}}{\text{Assets}}\right)_{bt} = \alpha_b + \beta_b \text{CCB}_t + \varepsilon_{bt} \qquad \forall b \in B \tag{6}$$

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. We should also 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 (6) 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 4 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.

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 5 Panel C and Panel D. These

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.

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.

I present evidence that banks seem to face borrowing constraints in the currency required to arbitrage. An increase in the cross-currency basis is associated with greater soles scarcity, while a decrease in the cross-currency basis is associated with greater dollar scarcity. This is shown in Table 6, which replicates the regressions of the previous section (Equations (4a) and (4b)) using interest rate spreads[14] and liquidity ratios. In aggregate, a 1pp increase in the cross-currency basis

[14] 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

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[15]. Analogously, a 1pp decrease in the cross-currency basis is associated with an increase between 0.4 and 0.6pp in the dollar spread and an increase between 1.6 and 3.8pp in the share of dollar liquid assets[16].

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 therefore, I do not claim causality. On one hand, estimating bank-level regressions of Table 6 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[17]. 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 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.

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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.

[15]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.

[16]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.

[17]Regressions for the interbank loans 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.

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 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:

$$CCB_{t-1}^{\text{Peru}} \times \text{Arb.Intensity}_b = \gamma_0 + \gamma_1 \text{CCB}_{t-1}^{ChMex} \text{Arb.Intensity}_b + X'_{b,t-1}\Theta + \psi_b + \upsilon_{b,t-1} \tag{7a}$$

$$y_{bft} = \alpha_0 + \alpha_1 \, \widehat{CCB_{t-1}^{\text{Peru}} \times \text{Arb.Intensity}_b} + \psi_{bf} + \psi_{ft} + X'_{b,t-1}\Psi + \varepsilon_{bft} \tag{7b}$$

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[18]; 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[19]; $X_{b,t-1}$ 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 (7a) and (7b) 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 the two Latin American currencies whose correlation with the USDPEN cross-currency basis is the strongest. As shown in Table 1, the average basis of USDCLP and USDMXN has a correlation of 0.51 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

[18] 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.

[19] 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.

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.[20]

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 banks arbitraging CIP deviations. 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.

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 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 and checks on the standard errors.

[20] 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.

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 reduce lending in soles by 26% and increase lending in dollars by 18%. In net terms, this represents a change in the currency denomination of the loans and a small change in total loans.

Table 7 shows the first-stage results for various specifications, including the baseline specification (Column 3). These results show that the instrument is statistically significant and highly stable across specifications. Its strong correlation with USDPEN cross-currency basis also indicates the absence of a weak instrument problem.

Table 8 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 and the share of dollar loans. The first four columns in both tables correspond to the OLS results, while the last four correspond to the IV results. The first-stage results for this specification are those in Column 3 of Table 7.

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.[21] 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

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

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

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 much the regression results. First, Table 9 shows that the results get even stronger when narrowing the sample of banks to only the largest four banks.[22] 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 10, which include dropping bank controls and adding fixed effects one-by-one. In general, Table 10 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 regarding the FX. As shown in Figure 3, a variable affecting CIP deviations across countries is the value of the dollar (i.e., the FX).[23] 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 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

[22] The largest differences regarding Table 8 derive from a larger coefficient on dollar lending (increases from 18.08% to 45.37%) after an increase of 1pp in the cross-currency basis, which leads to a 9.9% increase in total lending. With the baseline sample, total lending was merely 3.4%.

[23] 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.

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:

$$\left(\frac{\text{Deposits}}{\text{Assets}}\right)_{bt} = \alpha_b^0 + \alpha_b^1 \log(\text{FX})_t + \varepsilon_{bt} \qquad \forall b \in B \tag{8}$$

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

Table 11 shows the summary statistics of the estimated coefficients, splitting banks into three groups, depending on their arbitrage intensity. The table shows that the banks that arbitrage the most are not the most affected by the FX. The banks in the middle range of arbitrage intensity are those for which dollar deposits increase the most when the sol depreciates, while the banks in the low range of arbitrage intensity are those for which 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.

I confirm that the FX channel does not play an important role in explaining the bank lending results by adding the interaction between arbitrage intensity (-β) and log(FX). The results are displayed in Table 12.

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.[24] These constitute 50% of the loans given to firms in Peru. As Table 13 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 the baseline results are not driven by particular demands for specific types of loans or bank specialization in this.

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 14 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 and test a new channel of bank lending; the "arbitraging CIP deviations channel". I argue that, although the existence of CIP deviations implies that banks cannot fully arbitrage CIP deviations,

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

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 and I show this to be the case. I also 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 demonstrate that banks arbitraging CIP deviations shift the currency composition of their lending to firms. In particular, banks that use 1% more of their assets to arbitrage CIP deviations, decrease their lending in soles by 26% and increase their lending in dollars by 18% after a 1pp increase in the USDPEN cross-currency basis. Given that various studies have shown the importance of currency mismatches on real outcomes, this result casts new light on the possible real implications that CIP deviations can have on the real economy.

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

References

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

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

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

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

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

BCRP (2015, December). Reporte de inflacin. techreport.

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

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

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

Castillo, P., H. Vega, E. Serrano, C. Burga, et al. (2016). De-dollarization of credit in peru: the role of unconventional monetary policy tools. Technical report, Banco Central de Reserva del Perú.

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

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

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

Cremers, K. J. M., R. Huang, and Z. Sautner (2010, dec). Internal capital markets and corporate politics in a banking group. *Review of Financial Studies 24*(2), 358–401.

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

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

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

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

Humala, A. (2019). Corporate earnings sensitivity to fx volatility and currency exposure: evidence from peru. Technical report, Banco Central de Reserva del Perú.

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

Keller, L. (2019, jan). Capital Controls and Misallocation in the Market for Risk: Bank Lending Channel.

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

Liao, G. Y. (2020, jun). Credit migration and covered interest rate parity. *Journal of Financial Economics*.

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

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

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

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

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

Table 1: 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, but excluding the financial crisis (from December 2007 to July 2009). First, under "Peru", it shows the descriptive statistics for the USDPEN currency pair. 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. Second, under "Av.Latam", it shows 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). Finally, the last group focuses on 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 (although in terms of magnitude, Peru resembles more the average Latin American group). 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 (%)	-0.27	0.77	-2.12	1.98	77.00	
CCB >0 (%)	0.58	0.54	0.08	1.98	24.00	
CCB <0 (%)	-0.65	0.49	-2.12	-0.01	53.00	
$\lvert CCB\rvert$ (%)	0.63	0.50	0.01	2.12	77.00	
Δ_{1m} CCB (pp)	-0.04	0.75	-1.76	2.47	75.00	
$\Delta_{1m}\lvert CCB\rvert$ (pp)	0.54	0.52	0.01	2.47	75.00	
$\Delta_{12m}FX$ (%)	-3.53	3.02	-11.76	4.22	77.00	0.29
Av.Latam						
CCB (%)	-0.21	0.68	-1.90	1.41	77.00	0.38
CCB >0 (%)	0.48	0.44	0.00	1.41	28.00	
CCB <0 (%)	-0.61	0.42	-1.90	-0.00	49.00	
$\lvert CCB\rvert$ (%)	0.56	0.43	0.00	1.90	77.00	
Δ_{1m} CCB (pp)	-0.01	0.39	-1.45	1.22	75.00	
$\Delta_{1m}\lvert CCB\rvert$ (pp)	0.28	0.27	0.00	1.45	75.00	
$\Delta_{12m}FX$ (%)	-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	0.51
CCB >0 (%)	0.40	0.20	0.03	0.88	43.00	
CCB <0 (%)	-0.57	0.34	-1.47	-0.01	34.00	
$\lvert CCB\rvert$ (%)	0.47	0.28	0.01	1.47	77.00	
Δ_{1m} CCB (pp)	0.00	0.28	-0.63	0.71	75.00	
$\Delta_{1m}\lvert CCB\rvert$ (pp)	0.22	0.17	0.01	0.71	75.00	
$\Delta_{12m}FX$ (%)	-4.81	6.77	-22.00	9.07	77.00	0.30

Table 2: Summary Statistics of the Aggregate Banking System's Assets and Liabilities

This table shows descriptive statistics of the monthly time series of *aggregate* accounts of banks' main balance sheet components (i.e. data is summed across all banks). The statistics have been computed over a the sample between February 2005 and 2013 (excluding the global financial crisis). This is the same sample that will be used when doing the loan-level analysis of CIP deviations on bank lending. Each pair of columns show the mean and standard deviation for different variables. Column 1 and 2 show these statistics for the levels (in billion dollars using constant FX of Feb. 2005). Column 3 and 4 show these statistics for each asset (liability) component as a share of total assets (liabilities). Column 5 and 6 show the share of each item that is in dollars. Column 7 and 8 show the dollar component as a share of dollar total assets (liabilities). Column 9 and 10 do the same but with soles. Finally, the last column shows the number of observations (months) over which the statistics have been computed.

	Total (B USD)		% of Total		% in USD		USD/ Total USD (%)		PEN/ Total PEN (%)		
	Mean	S.D	Mean	S.D	Mean	S.D	Mean	SD	Mean	SD	N
Assets	42.2	17.2	100.0	0.0	54.5	7.5	100.0	0.0	100.0	0.0	77.0
All Credit	26.4	11.4	61.7	2.9	59.1	9.2	66.7	3.1	55.2	7.2	77.0
Commercial	17.1	7.4	39.9	1.7	69.5	7.1	51.2	4.0	26.6	3.8	77.0
Corp-Medium Firms*	14.0	5.7	33.1	1.2	73.9	4.7	45.4	4.3	19.1	2.3	77.0
Consumption	4.6	2.2	10.4	1.3	19.5	8.4	3.5	0.8	18.5	1.7	77.0
Mortgages	3.9	1.9	8.9	0.7	69.3	20.0	11.1	1.2	5.7	3.6	77.0
Cash	9.0	4.4	21.0	3.7	78.5	14.1	29.6	2.7	9.9	6.8	77.0
Investment	5.4	1.8	13.8	3.5	21.4	7.5	5.2	1.6	24.7	8.2	77.0
CB Cert.Dep., ST Gvt Bonds	4.0	1.7	9.9	3.3	10.4	8.2	1.7	1.1	20.1	7.5	77.0
Liabilities	38.2	15.5	100.0	0.0	59.0	5.4	100.0	0.0	100.0	0.0	77.0
Deposits	28.2	10.4	75.1	3.6	54.7	8.2	69.5	7.3	82.3	3.2	77.0
Checkings + Savings	13.8	5.6	36.1	1.2	53.4	6.2	32.7	1.6	41.0	1.8	77.0
Term Deposits	13.0	4.3	35.3	3.3	54.5	10.2	32.6	6.1	38.5	2.5	77.0
Short-term	11.4	3.6	31.0	3.4	52.9	9.7	27.8	5.6	35.0	2.5	77.0
Other	1.3	0.5	3.6	0.6	66.9	10.3	4.2	1.0	2.8	0.4	77.0
Obligations w/ Fin. System	4.9	2.9	11.9	3.1	88.0	8.6	18.3	6.4	3.6	2.9	77.0
Foreign Fin. System	4.0	2.9	8.9	4.2	98.6	1.0	15.7	8.3	0.3	0.2	77.0
Short-term	1.7	1.1	4.2	1.7	99.4	0.4	7.2	3.3	0.1	0.0	77.0
Local Fin. System	0.9	0.3	3.0	1.9	49.0	24.8	2.7	2.1	3.3	3.0	77.0

* Corp- Medium Firms: These are in the loan-level dataset that will be used later

Table 3: 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 6 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 $\hat{\beta}$						
$\hat{\beta}$	-1.69	-1.62	1.69	-4.82	0.00	873
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 4: Summary Statistics by β

This table presents descriptive statistics of the balance sheet of banks in Peru for the sample period, split by arbitrage intensity ($\hat{\beta}_b$)). The split has been done based on modes. Broadly speaking, there are three groups of banks. The first group of banks comprises banks that do not engage much in forward contracts and hence, do not arbitrage much. These have $-\hat{\beta}$ between 0 and 0.2. These also are the smallest group of banks. The second group, arbitrages significantly more ($0.2 \leq \hat{\beta} \leq 2.5$) and is composed by larger banks. The last group, although arbitrages more than the second, is relatively smaller than the second group.

	All sample									Largest Banks					
	Low $\hat{\beta}$			Medium $\hat{\beta}$			Large $\hat{\beta}$			Lower $\hat{\beta}$			Larger $\hat{\beta}$		
	$0 \leq \hat{\beta} < 0.2$			$0.2 \leq \hat{\beta} < 2.5$			$2.5 < \hat{\beta}$			$0 \leq \hat{\beta} < 2$			$2 \leq \hat{\beta}$		
	N	Mean	Sd	N	Mean	Sd	N	Mean	Sd	N	Mean	Sd	N	Mean	Sd
$\hat{\beta}$	394	-0.09	0.07	231	-1.95	0.31	248	-4.01	0.61	154	-1.75	0.13	154	-2.83	0.47
Net Matched Position (Million USD)	394	0.53	3.24	231	18.15	207.54	248	3.86	168.93	154	-8.01	232.71	154	-12.91	220.65
|Net Matched Position (Million USD)|	394	1.34	2.99	231	152.29	141.82	248	117.18	121.52	154	177.52	150.00	154	163.44	148.21
$\lvert$Net Matched Position$\rvert /Assets(\%)$	394	0.22	0.70	231	1.98	1.69	248	6.17	6.02	154	1.91	1.68	154	2.65	2.65
Total Assets (Bill. USD)	394	0.89	0.60	231	10.06	7.74	248	4.06	5.31	154	12.61	8.19	154	7.84	4.99
ROA (%)	32	2.38	1.86	18	2.17	0.55	20	1.01	1.55	12	2.07	0.61	12	2.51	0.33
PEN Liq. (% Assets)	394	9.87	4.20	231	12.36	4.26	248	17.28	8.90	154	13.45	4.45	154	12.29	4.13
USD Liq. (% Assets)	394	9.28	5.54	231	17.38	4.04	248	19.69	5.41	154	17.74	4.37	154	16.85	3.47
PEN Cred. (% Assets)	394	47.44	20.79	231	22.63	7.00	248	24.04	7.62	154	19.62	5.52	154	27.39	6.66
USD Cred. (% Assets)	394	22.47	16.62	231	33.75	3.79	248	31.87	8.81	154	35.30	2.32	154	33.09	4.91
PEN Dep. (% Assets)	394	42.90	14.00	231	29.86	4.06	248	29.73	8.59	154	28.60	4.11	154	33.26	3.49
USD Dep. (% Assets)	394	24.30	15.83	231	40.69	9.05	248	40.03	9.25	154	42.02	9.19	154	38.42	8.65

Table 5: 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. The stage of the arbitrage to which the variable belongs is stated in bold fonts. Variables are written as percentage of total assets (in the 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 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 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 reported in parentheses and 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 6: 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 7: 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 (7a). The dependent variable for all specifications is $CCB_{t-1}^{Peru} \times (-\hat{\beta})$. 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 7a). 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)
$\text{CCB}_{t-1}^{\text{Chile,Mex}} * (-\hat{\beta})$	0.787***	0.577***	0.557***
	(5.05)	(4.14)	(3.95)
Bank Controls	No	No	Yes
Bank FE	No	Yes	Yes
F	25.48	17.11	15.62
Observations	1325323	1325323	1325323

Table 8: 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 7b. The first four columns show the OLS estimates while the last four show the IV estimates. 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(PEN)	Log(USD)	Log(Total)	Ratio
$\text{CCB}_{t-1}^{\text{Peru}} * (-\hat{\beta})$	-5.644**	2.818**	0.240	0.301**	-25.70***	18.08***	3.436**	1.550***
	(-2.51)	(2.32)	(0.54)	(2.56)	(-3.24)	(3.34)	(2.00)	(3.25)
Firm * Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank * Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1325323	1325323	1325323	1325323	1325323	1325323	1325323	1325323
N Firm Cluster	18,269	18,269	18,269	18,269	18,269	18,269	18,269	18,269
N Date Cluster	77.00	77.00	77.00	77.00	77.00	77.00	77.00	77.00
Adjusted R2	0.75	0.81	0.72	0.82	-0.00	-0.00	0.00	-0.00

Table 9: Effect of Arbitraging CIP deviations on Bank Lending: Baseline specification for Largest Banks

This table presents the baseline results of the effect of arbitraging CIP deviations on bank lending but for the subsample of the four largest banks. The specification is given by Equation 7b. The first four columns show the OLS estimates while the last four show the IV estimates. 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(PEN)	Log(USD)	Log(Total)	Ratio
$\text{CCB}_{t-1}^{\text{Peru}} * (-\hat{\beta})$	-11.17***	8.727**	1.521	0.830***	-37.53***	45.37***	9.942***	3.427***
	(-3.09)	(2.55)	(1.31)	(3.17)	(-3.14)	(4.12)	(3.19)	(3.80)
Firm * Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank * Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1035629	1035629	1035629	1035629	1035629	1035629	1035629	1035629
N Firm Cluster	16,728	16,728	16,728	16,728	16,728	16,728	16,728	16,728
N Date Cluster	77.00	77.00	77.00	77.00	77.00	77.00	77.00	77.00
Adjusted R2	0.74	0.80	0.73	0.81	-0.00	-0.01	-0.00	-0.01

Table 10: Effect of Arbitraging CIP deviations on Bank Lending: Alternative Specifications

This table presents alternative specifications of the second-stage baseline results of arbitraging CIP deviations on bank lending. Each coefficient corresponds to the instrumented $\text{CCB}_{t-1}^{Peru} * (-\hat{\beta})$ from the previous tables. The first row shows the baseline second-stage regression shown in Table 8. The second row continues to have all of the fixed effects, but drops all bank controls. Starting from the third row, I drop all controls and add one fixed effect at a time. The third row corresponds to the plain regression without controls and without fixed effects. The fourth row adds firm fixed effects. The fifth row adds bank fixed effects to the fourth-row specification. Finally, the last row adds month fixed effects to the fifth-row specification. 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
Baseline	-25.70***	18.08***	3.44**	1.55***
	(-3.24)	(3.34)	(2.00)	(3.25)
Baseline w/o Controls	-27.43***	13.20***	1.27	1.38***
	(-3.49)	(3.09)	(0.89)	(3.27)
No FE, No Controls	-38.22***	26.49***	-5.94**	2.96***
	(-3.77)	(2.87)	(-2.62)	(3.49)
Firm FE, No Controls	-34.49***	3.84	-11.90***	1.76***
	(-4.52)	(1.24)	(-3.77)	(4.62)
Firm FE, Bank FE, No Controls	-33.82***	9.62***	-8.12***	1.98***
	(-4.13)	(3.12)	(-2.93)	(4.52)
Firm FE, BankFE, Date FE, No Controls	-27.81***	13.54***	1.60	1.44***
	(-3.98)	(3.44)	(1.16)	(3.80)

Table 11: 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 6. The sensitivity of bank deposits to changes in FX has been estimated using Equation 8.

	Low -$\hat{\beta}$ $0 \leq -\hat{\beta} < 0.2$		Medium -$\hat{\beta}$ $0.2 \leq -\hat{\beta} < 2.5$		Large -$\hat{\beta}$ $2.5 < -\hat{\beta}$	
	Mean	Sd	Mean	Sd	Mean	Sd
$-\hat{\beta}$	0.09	0.08	1.95	0.37	4.00	0.64
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 12: 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 (-$\hat{\beta}$). The first four columns do not include 1-month lagged bank-month controls while the last columns add 1-month lagged bank-month controls. 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).

	Without Controls				With Controls			
	Log(PEN)	Log(USD)	Log(Total)	Ratio	Log(PEN)	Log(USD)	Log(Total)	Ratio
$\mathrm{CCB}_{t-1}^{\mathrm{Peru}} * (-\hat{\beta})$	-19.31***	13.06***	3.335**	1.037***	-18.36***	18.01***	5.652***	1.224***
	(-2.87)	(2.88)	(2.29)	(2.75)	(-2.73)	(3.14)	(2.91)	(2.87)
$\log(\mathrm{FX})_{t-1} * (-\hat{\beta})$	-1.767***	0.326	-0.128	0.0804***	-1.980***	0.270	-0.229*	0.0917***
	(-4.18)	(1.11)	(-1.23)	(3.42)	(-4.85)	(0.79)	(-1.87)	(3.64)
Firm * Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank * Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Controls	No	No	No	No	Yes	Yes	Yes	Yes
Observations	1207390	1207390	1207390	1207390	1207390	1207390	1207390	1207390
N Firm Cluster	16,995	16,995	16,995	16,995	16,995	16,995	16,995	16,995
N Date Cluster	75	75	75	75	75	75	75	75

Table 13: Effect of Arbitraging CIP deviations on Bank Lending: Baseline using only commercial loans

This table shows the second stage results for the baseline regression when constraining the sample to only commercial loans (prestamos). 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).

	With Controls				Without Controls			
	Log(PEN)	Log(USD)	Log(Total)	Ratio	Log(PEN)	Log(USD)	Log(Total)	Ratio
$CCB_{t-1}^{Peru} * (-\hat{\beta})$	-30.46***	20.33***	-0.788	2.171***	-31.22***	22.06***	-0.426	2.277***
	(-3.20)	(2.73)	(-0.44)	(3.16)	(-3.13)	(2.76)	(-0.24)	(3.14)
Firm * Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank * Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Controls	No	No	No	No	Yes	Yes	Yes	Yes
Observations	657337	657337	657337	610023	657337	657337	657337	610023
N Firm Cluster	12,346	12,346	12,346	11,818	12,346	12,346	12,346	11,818
N Date Cluster	77	77	77	77	77	77	77	77

Table 14: Standard Errors Robustness Check: Using Different Clusters

This table checks the validity of the standard errors in the baseline regression specification. The first row reports the coefficients of the second-stage baseline regression for the four dependent variables used. Under "standard errors" I report the standard errors of various clusters. The first standard errors reported are those for the baseline regression and are shaded in gray. It uses two-way clusters and clusters by firm and date. I do not cluster by bank in the baseline regression because there are 11 banks in total and clustering requires more clusters to be consistent. The following lines show the standard errors using alternative clusters. The name of the cluster is indicated on the table. The corresponding number of clusters in the baseline regression for each cluster variable is displayed at the bottom of the table. Next to each standard error, the ***, ** and * denote significance at 1%, 5% and 10% respectively.

	Log(PEN)	Log(USD)	Log(Total)	Ratio
Baseline Coefficient	-25.70	18.08	3.44	1.55
Standard Errors:				
Baseline	7.93***	5.42***	1.72**	0.48***
Bank Cluster	5.52***	10.13	3.01	0.60**
Bank and Date Cluster	7.60***	9.00*	2.56	0.60**
Firm Cluster	3.32***	3.01***	1.35**	0.22***
Firm and Bank Cluster	4.91***	8.41*	2.59	0.51**
Number of Clusters				
N. Bank Clusters	12.00	12.00	12.00	12.00
N. Date Clusters (N.Months)	77.00	77.00	77.00	77.00
N. Firm Clusters	18,269.00	18,269.00	18,269.00	18,269.00

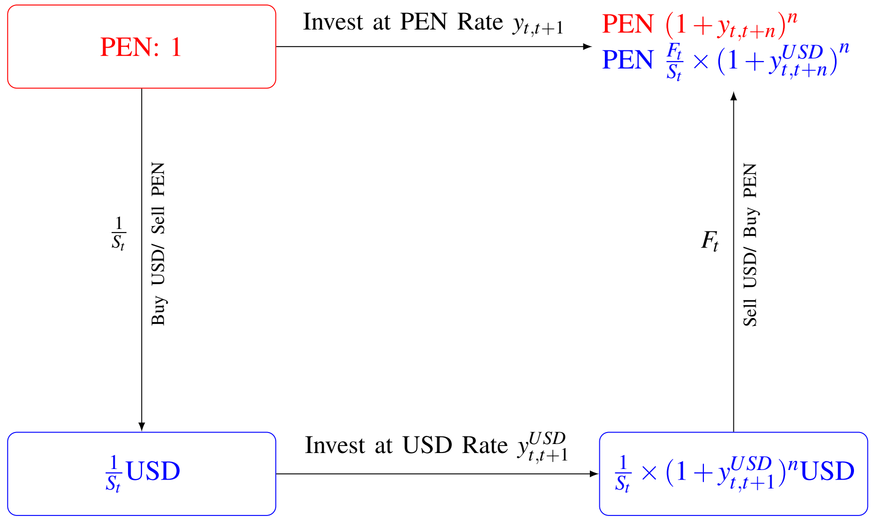
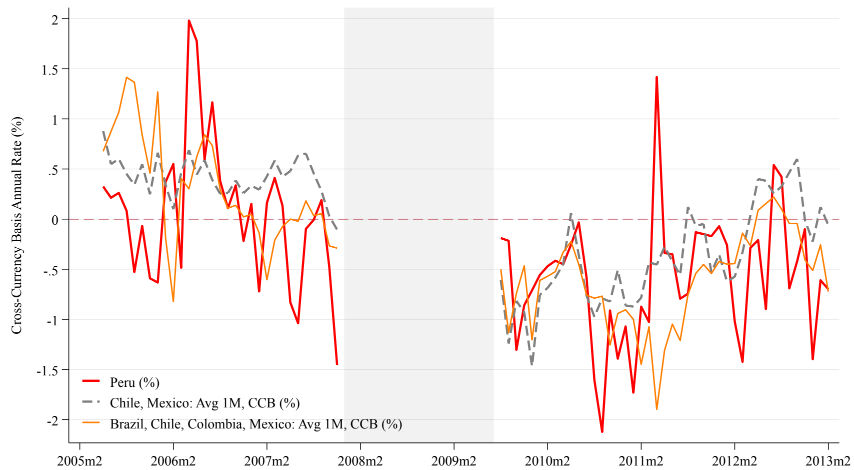
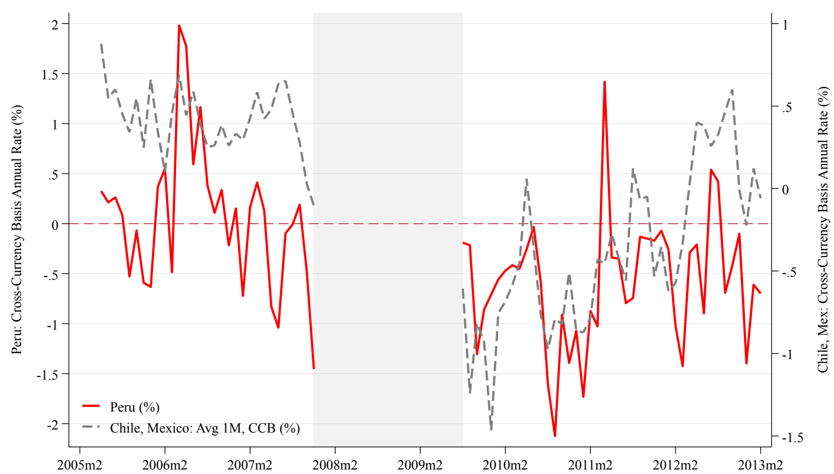


Figure 1: Example of Covered Interest Rate Parity (CIP)

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: $1+y_{t,t+1} = \frac{F_t}{S_t} \times (1+y^{USD}_{t,t+1})$.



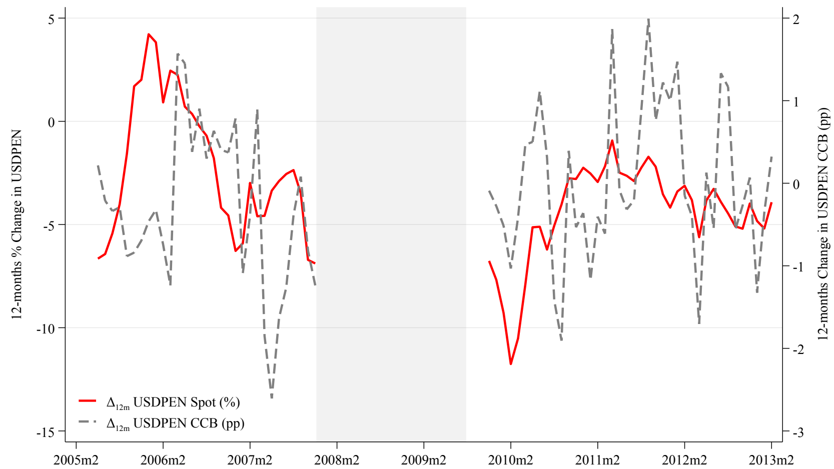
Panel A: Peru and other Latin American countries



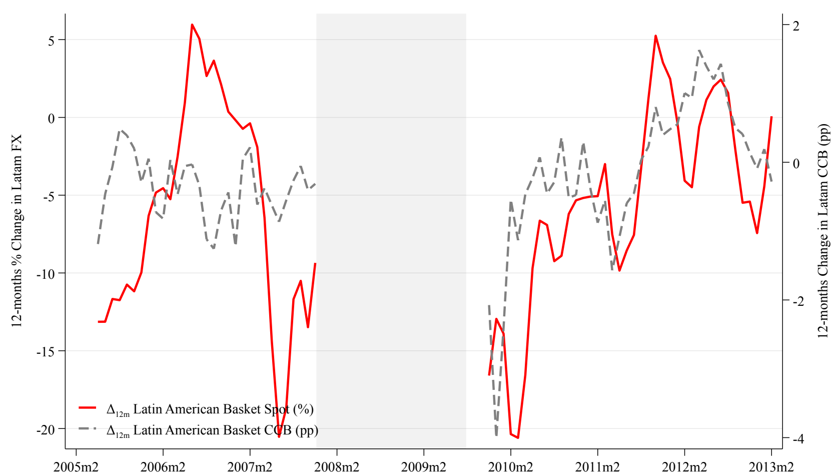
Panel B: Peru and Average of Mexico and Chile

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

Panel A 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. This is seen on Panel B, which plots the Peru's cross-currency basis against the average basis between 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



Panel A: USDPEN FX and Cross-Currency Basis in Peru

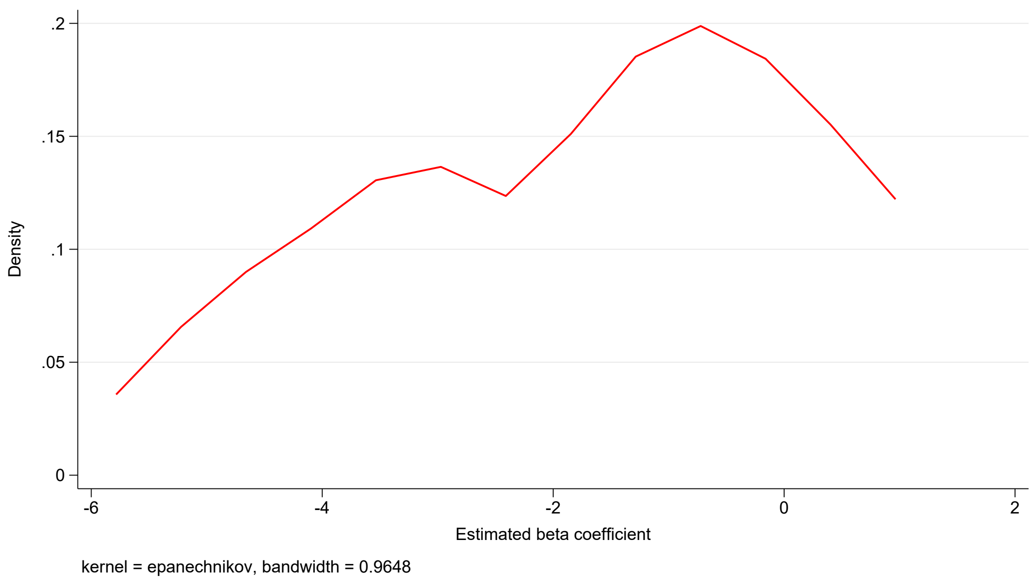


Panel B: FX and Cross-Currency Basis in Latin America

Figure 3: CIP deviations and FX

Panel A plots the yearly changes in USDPEN cross-currency basis against the yearly changes in FX. Panel B does the same for the "Latin American" basket. The cross-currency basis of the "Latin American" basket is the average cross-currency basis of USDBRL, USDCLP, USDCOP and USDMXN. In both cases, 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 positive changes in the 1-year FX corresponds to depreciations of the local currency. Hence, the positive correlation between the cross-currency basis and the FX shows that the local currency depreciates as the cross-currency basis increases. 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

Figure 4: Smoothed density of the estimated $\hat{\beta}$ coefficients



APPENDIX

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 **??**). 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:

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

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

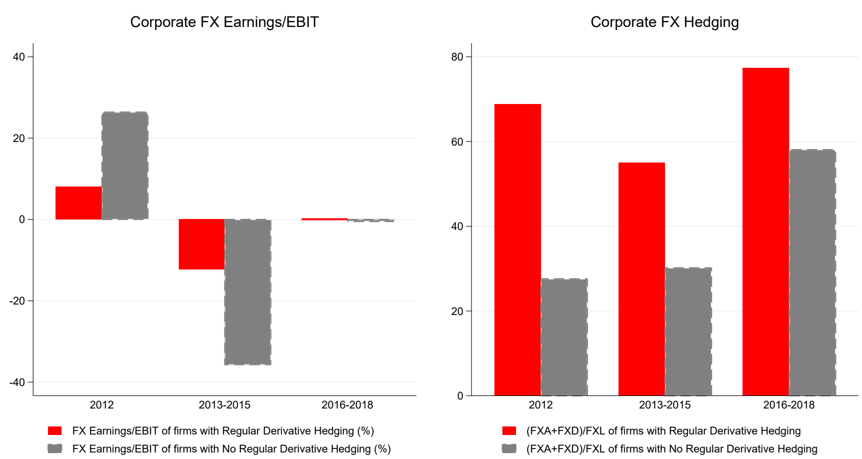
B Concerns regarding analyzing credit supply and demand in Peru between late 2013 and 2016

The sample in this paper ends in February 2013 to prevent the results from being affected by various regulations and confounders. In this section I explain the concerns regarding studying credit supply and demand between late 2013 and early 2016.

The concerns are linked to the significant depreciation of the sol during these years. After the Taper Tantrum in 2013, there has been a significant depreciation of local currencies across emerging markets. In Peru, the sol depreciated 37% between 2013 and 2016. This significant depreciation can lead to changes in behavior and preferences of various economic agents. Moreover, it also led the Peruvian government to impose a series of regulations at the same time. Therefore, studying credit dynamics during this period is prone to various confounders coming from reactions to the FX as well as regulations, making it difficult to isolate the effects on credit of specific interventions. In the case of this paper, it will be difficult to isolate the effects of arbitraging CIP deviations.

Such large depreciation affected firms that had been borrowing in USD but that were not hedging. Humala (2019) looks at the financial statements of Peruvian firms that trade in the stock exchange and they see that most were not hedging during the currency appreciation of 2012 and hence had losses of 36% of their EBIT for firms that were not hedging, and 12% for those that were partly hedging during 2013-2015. Subsequently, firms increased their hedging by either using derivatives or reducing their USD borrowing and therefore between 2016 and 2018 they didn't seem to have almost any profit or loss coming from FX. This is shown in Figure A.1.[25]

Figure A.1: Firms FX losses and hedging



Source: Data from Figures 4 and 5 in Humala (2019)

[25] I constructed with the data shown in Figures 4 and 5 from Humala (2019).

In light of the losses that occurred, the Central Bank launched a series of de-dollarization measures in order to reduce financial vulnerability as USD was expected to appreciate (BCRP, 2015).

As Castillo et al. (2016) explain, the main features of the de-dollarization program took place between 2013 and 2016. Limits were set to mortgage and vehicle loans, as well as for total loans to the private sector in foreign currency.[26] More specifically, the Central Bank began its de-dollarization policies in October 2013, by setting increasing reserve requirements for banks whose stock of total lending to the private sector grew in excess of 5%, 10% and 15%, relative to their own credit outstanding in September 2013. These measures were reinforced in December 2014, when the system was replaced by new targets of *reduction* in the stock of total lending in foreign currency. Under this regulatory framework, banks face higher reserve requirements unless they reduced their total lending balances by 5% by June 2015, and by a total of 10% by December 2015, relative to the balances of September 2013. Finally, a reduction goal of 20% was set for December 2016.

Although it is difficult to disentangle the effect of this regulation itself from the likely increase in risk aversion faced by economic agents after the 37% depreciation of the soles after the taper tantrum, the result in this period was a severe drop in households and firms' foreign currency borrowing from banks. The share of USD credit given by banks decreased from almost 60% in 2013 to 30% in 2016.

This depreciation shock and the various regulations that were enacted during this time because of the depreciation make it difficult to provide credible estimates on bank lending. Unfortunately, using the cross-section of banks does not completely alleviate the problems given that as banks had different dollar lending balances, the limits set also affected banks in different degrees. Hence, I abstain from using this period in my analysis and end my sample on February 2013.

[26] As a brief summary, limits to mortgage and vehicle loans in foreign currency were first established in March 2013. This first package established increasing reserve requirements for banks whose stock growth of these loans increased by more than 10% or 20%. In December 2014, new limits were set to reduce the stock of such loans. This was again enforced by charging a higher reserve requirement for banks that did not meet the schedule of stock reduction. The final aim was to reduce these loans to 70% of the stock corresponding to early 2013, by the end of 2016 (Castillo et al., 2016)