Arbitraging Covered Interest Rate Parity Deviations and Bank Lending

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I propose and test a new channel through which bank lending is affected in an emerging markets setting. This channel is that when banks arbitrage covered interest rate parity (CIP) deviations, they need to borrow in a particular currency. In the presence of borrowing frictions, they shift part of the resources used to lend to households and firms to fund their arbitrage activities. I exploit differences the abilities of Peruvian banks to arbitrage CIP deviations to show that banks that have greater ability to arbitrage reduce their lending in the currency they need to fund their CIP arbitrage. This is compensated by lending in a different currency. Therefore, arbitraging CIP deviations lead to changes in the currency composition of lending.

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I. Introduction

In emerging economies, households and firms have significant currency mismatches between their assets and liabilities. The main source of these mismatches arises from borrowing in foreign currency from local banks. Numerous studies have shown that the greater exposure to exchange rate (FX) risk associated with currency mismatches has had significant effects on the real economy after sudden changes in the FX. Such effects include significant reductions in employment, investment and growth after depreciation shocks.[1]

At the same time, economies have been facing a seemingly unrelated phenomenon: significant arbitrage opportunities in FX markets.[2] These arbitrage opportunities are known as covered interest rate parity (CIP) deviations. Under CIP, the return of lending a particular currency at its risk-free rate (lending directly) should equal the return of replicating the same transaction by lending at the risk-free rate of a *different* currency but using derivative contracts to hedge the currency risk (also called lending synthetically). When CIP does not hold, or in other words, when there are deviations from CIP, an arbitrageur would obtain risk-less profits. The spread between lending synthetically and lending directly measures these profits and is called cross-currency basis.[3]

In this paper, I propose and test a new channel through which bank lending is affected. To the best of my knowledge, this is the first paper to propose a channel through which arbitraging CIP deviations can affect firms and households by either affecting total bank lending or the currency composition of bank lending. Using an emerging market setting, I show that by arbitraging CIP deviations, banks shift the currency composition of their lending to firms. Up to now, the literature on CIP deviations has focused on understanding CIP deviations from an asset pricing point of view. This paper tries to bridge the gap between asset pricing and corporate finance by showing that CIP deviations can affect the currency composition of bank lending, which at the same time is known for affecting firms and the real economy.

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[1] See Aguiar (2005); Kim et al. (2015); Verner and Gyöngyösi (2020)

[2] See Baba et al. (2008); Baba and Packer (2009); Coffey et al. (2009); Mancini-Griffoli and Ranaldo (2011); Du et al. (2018)

[3] For example, when the risk-free rate of currency i is lower than its synthetic rate, an arbitrageur would borrow currency i synthetically and lend it directly at its risk-free rate.The opposite holds when the rate of the direct transaction is lower than the synthetic one. That is the synthetic rate minus the risk-free rate (the direct rate).

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The main argument behind the channel is the following. Banks, who are the natural CIP deviations arbitrageurs, attempt to arbitrage CIP deviations when these exist. Arbitraging CIP deviations requires them to borrow in a particular currency, which is dictated by the sign of the cross-currency basis.[4] When banks have constraints to expand their borrowing in that currency, they face a trade-off. Either they use their current funding capacity to fund their core business or use these funds to arbitrage CIP deviations. Although there might be important costs from switching from their core business to arbitrage activities, it is still likely that banks end up demanding higher mark-ups in their core businesses to account for their higher opportunity cost. Given that the core business of banks is predominantly commercial and household lending, CIP deviations could induce banks to increase the rates charged when lending in the scarce currency. As a result, firms and households will have incentives to change the currency composition of their borrowing.

To help illustrate this mechanism, consider the case of a Peruvian local bank attempting to arbitrage CIP deviations when the cross-currency basis is positive. That is, the soles (the Peruvian currency) risk-free rate is lower than the synthetic soles rate. In this case, the bank would profit from borrowing soles at the risk-free rate and lending soles synthetically. In the face of difficulties expanding its soles borrowing to fund its arbitrage activities, the bank's trade-off is whether to use soles deposits that were going to be used to lend in soles to households and firms, or use these soles to lend them synthetically as part of the CIP arbitrage. If the bank decides to use its scarce soles deposits to lend soles to households and firms, it is missing out on a risk-free profit that could be made by arbitraging CIP deviations. Hence, relative to a scenario without CIP deviations, the bank will likely increase its lending soles rate to reflect its higher opportunity cost. As a result, households and firms would borrow less in soles and more in dollars. This is particularly the case in emerging economies, where many of these economies are partially dollarized and local banks also lend in dollars.[5]

[4] When the cross-currency basis is positive, the synthetic rate is higher than the risk-free rate counterpart. In this case, arbitraging CIP deviations involves borrowing at the risk-free rate and lending at the synthetic rate. The converse occurs when the cross-currency basis is negative. In this case, the synthetic rate is lower than the risk-free rate and the arbitrageur profits from borrowing at the synthetic rate and lending at the risk-free rate. Applying this to the case of soles (the Peruvian currency), borrowing soles synthetically means borrowing dollars at the dollar risk-free rate, converting these to soles while entering into a swap to convert the soles back to dollars to pay the dollar loan once the loan matures.

[5] The opposite occurs when the cross-currency basis is negative. In this case, the bank profits when borrowing soles synthetically and lending them at the risk-free rate. Borrowing soles synthetically involves borrowing dollars at the dollar risk-free rate, converting the dollars to soles while simultaneously engaging in a swap to convert the soles loan

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In this paper, I empirically test this channel by studying the relationship between CIP deviations and bank lending in Peru between 2005 and 2013 (excluding the financial crisis).[6] In this sample period, nearly 60% of the amount banks lent in Peru was in dollars. At the same time, Peru also experienced large CIP deviations: the difference between the soles risk-free rate and its synthetic counterpart has oscillated between -2% and 2% without including the crisis (-10% to 5% once the crisis is included).

Using this context, I find that banks seem to arbitrage CIP deviations but that there are important heterogeneities in how much banks can arbitrage. In a context where banks cannot easily expand their balance sheets to fund their arbitrage activities, I find that arbitraging CIP deviations crowds-out the bank lending division in the currency that is required to perform the arbitrage. Banks seem to substitute this credit with a different currency. 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 35% and increase their dollar lending by 22% after a 1pp increase in the USDPEN cross-currency basis.

To reach these conclusions, I proceed in three complementary steps. First, I start by studying whether banks' activities suggest that they attempt to arbitrage CIP deviations and if they do, whether there are differences across banks in the degree they can arbitrage. I find that the transactions banks do in the money market and in the FX market are consistent with banks attempting to arbitrage CIP deviations.[7] However, an important finding is that not all banks can arbitrage in

proceeds to dollars to pay back the dollar debt. Therefore, if the bank faces constraints expanding its dollar borrowing to fund its arbitrage activities, the bank's trade-off is whether to use dollar deposits that were going to be used to lend in dollars to households and firms, or use these dollars to convert them to soles and invest in soles risk-free assets as part of the CIP arbitrage. Given the higher opportunity cost to lending dollars to households and firms, banks might increase the lending rate in dollars and therefore, dissuade firms and households from borrowing in dollars.

[6] I do not include the period beyond 2013 because this is a period where there are many confounders that can severely affect the analysis. First, from January 2013 to January 2016, the soles depreciated 37%. This is partly attributed to the US Federal Reserve's taper tantrum. Humala (2019) shows even large firms had FX losses that were in the range of 14-38% of their earnings before interest and taxes (EBIT) on average in the years 2013 to 2015. As a response, on one hand, firms might not want to borrow more in dollars as their risk aversion could have been particularly high in this period of time. On the other hand, the Central Bank of Peru implemented a de-dollarization policies that intended to reduce dollar bank lending. Most likely, these two forces resulted in credit in dollars being substituted for credit in soles.

[7] The correlations between the cross-currency basis and the spot, forward and money market transactions are what one expects them to be. As the cross-currency basis increases and it becomes more profitable to borrow soles and lend soles synthetically, banks borrow more soles in the money market. They also lend more soles synthetically: they purchase more dollars in the spot market, invest in more short-term dollar assets and sell more dollars in the forward

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the same degree. 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. This heterogeneity across banks will be helpful in the third step (described below), when I exploit this cross-section variation to compare the response of bank lending to an increase in CIP deviations across banks of different "arbitrage intensities."

Second, to understand whether banks' arbitrage activities could be affecting other business lines, I analyze whether banks face funding constraints at the time of arbitraging CIP deviations. I find that this is the case. In particular, I find that liquidity becomes scarcer or more expensive in the currency that is needed to arbitrage the basis. Importantly, banks' own arbitrage transactions can tighten the liquidity constraints. In this situation, banks can reallocate resources internally, effectively be reallocating liquidity away from their lending division to fund the currency required to perform the arbitrage. In the next step, I study whether it seems the lending division of banks could have been affected by arbitraging CIP deviations.

Third, I study its impact of arbitraging CIP deviations on bank-lending in soles and dollars. An important building block for this third step is the finding that banks are heterogeneous in their abilities to arbitrage CIP deviations. More specifically, I study the lending behavior in dollars and soles of banks that arbitrage more[8] relative to those that arbitrage less after a change in the cross-currency basis. Given that more than 70% of the firms in my sample have multiple bank relationships, I use a *within firm-month* analysis. In sum, my results stem from simultaneously comparing (1) the lending of the *same bank to the same firm* at different levels of CIP deviations and (2) the lending of high arbitrage-intensive banks relative to less arbitrage-intensive ones.

The baseline regression addresses for various aspects that could be affecting the relationship between arbitraging the cross-currency basis and the composition of bank lending. First, given that CIP deviations are endogenous, it is important to highlight that I do not study the effect of CIP deviations themselves, but the effect of *arbitraging* CIP deviations on bank lending. Given that *arbitraging* CIP deviations require a specific set of transactions, these are more likely to capture

market. Similarly, when the cross-currency decreases, banks invest more in soles short-term assets. At the same time, they borrow more synthetic soles. That is, they borrow more dollars in the money market and from foreign banks.

[8] I define that a bank can "arbitrage more" when they allocate 1% more of their assets to arbitraging CIP deviations after a 1pp increase in the cross-currency basis.

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the link with CIP deviations than CIP deviations themselves. Second, the heterogeneity across banks in terms of how much they can arbitrage also alleviates concerns regarding the correlation between CIP deviations and other macroeconomic factors as these will be "differenced away" as long as they affect banks equally. However, given banks can be heterogeneous, not only I use bank-month controls and bank fixed effects, but I also re-estimate the regressions using a set of very similar banks. I also dedicate one section of the paper to exploring the possible biases caused the correlation between basis and the FX, and I find that the FX does not affect the results. Third, the inclusion of firm-month fixed effects controls for changes in aggregate economic conditions affecting firms' investment opportunities while additional firm-bank fixed effects controls for specific bank-firm relationships. Lastly, but importantly, the baseline model instruments the USDPEN cross-currency basis with that of other Latin American countries so that CIP deviations are not related to banks' activities in the FX market that can be correlated with their lending activities. This also helps to eliminate the effects of shocks specific to Peru that otherwise could drive the results.

I complement these results with various robustness checks that include redoing the analysis using alternative model specifications and various checks on the standard errors. I find that the results are very similar to the baseline model. I also complement the baseline results with varying firm samples as well as changing the sample to focus only on the main type of loans (commercial loans). I find that the results hold for all the different sizes of firms, although they are the strongest and largest for the medium-sized firms. They also hold when the sample only holds the same type of loan, and therefore the results are not biased by loan type.

There are two different ways in which these results can be interpreted. So far, for brevity and to avoid confusion, I have presented the results by arguing that arbitraging CIP deviations affect the currency composition of bank lending. More precisely, what this paper shows is that by engaging in transactions that are equivalent to arbitraging CIP deviations, banks shift the currency composition of their lending. Yet, these transactions are also exactly the same banks do when hedging their balance sheets. Particularly in emerging markets, regulation often forces banks to match the currency of their assets and liabilities. Then, when banks borrow in dollars but lend in soles, for example, banks are first selling dollars in the spot market to obtain cash in soles to lend, and

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then, are buying dollars forward to hedge the currency risk. Banks may decide their actions on how to hedge the currency risk based on the profitability of the cross-currency basis. When the cross-currency risk is positive or increasing, banks may decide to borrow in soles and lend in dollars while buying dollars spot and selling dollars forward. These transactions are exactly equivalent as the ones required to arbitrage CIP deviations. Hence, in this paper, I do not distinguish whether banks are hedging FX risk or actually just arbitraging CIP deviations. It is likely to be both and in fact, banks can decide their hedging strategies based on the profitability of the cross-currency basis. However, for brevity, I refer to the effects of the transactions required to arbitrage CIP deviations on bank lending as the effects of "arbitraging" CIP deviations on bank lending.

This paper makes two contributions to the literature. A first contribution is that, to the best of my knowledge, this is the first paper to propose and empirically test a new channel through which, by arbitraging CIP deviations, banks adjust the currency composition of their lending portfolios. This complements the existent literature on CIP deviations, which has focused on documenting that CIP deviations exist (Baba et al., 2008; Baba and Packer, 2009; Coffey et al., 2009; Mancini-Griffoli and Ranaldo, 2011; Du et al., 2018), why they exist (Du et al., 2018; Borio et al., 2018; Rime et al., 2020; Wallen, 2019)[9] and their relationship with other asset prices, such as the dollar (Avdjiev et al., 2019) and credit spreads of corporate bonds (Liao, 2020).

By showing that banks change the currency composition of their lending when they arbitrage CIP deviations, this paper complements this literature as it highlights that previous work on CIP deviations is not only important for asset pricing[10] but it can have significant implications for households and firms' currency mismatches. At the same time, understanding the sources of these mismatches is relevant because it is well documented that changes in currency composition of debt have first order real effects; including changes in sales, bankruptcy (Kim et al., 2015), investment

[9]Du et al. (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 et al., 2018), unaccounted real marginal funding costs (Rime et al., 2020) and imperfect competition (Wallen, 2019).

[10]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.

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(Aguiar, 2005), as well as spillover effects - through changes in local demand- to other agents in the economy (Verner and Gyöngyösi, 2020).

A second contribution of this paper is that it 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 et al., 1997; Houston and James, 1998; Campello, 2002; Ashcraft and Campello, 2007; Cremers et al., 2010) and global banks (Cetorelli and Goldberg, 2012a,b). Evidence of reallocation of funds within a bank in a single country (Gilje et al., 2016; Ben-David et al., 2017) 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.

The previous two contributions are likely the result of trying to address three main challenges that arise when studying the relationship between arbitraging CIP deviations and local bank lending. A first challenge is that, in addition to obtaining access to a credit registry, one needs to access data containing the FX transactions of banks. Both of these sets of data are confidential and hence, difficult to obtain. In this paper, I use confidential data that banks in Peru report to the Peruvian bank regulator (SBS after its Spanish acronym). A nice feature of using data from Peru is that, to check compliance with hedging regulation, banks constantly report to the regulator their FX transactions. A second challenge is that aggregate economic conditions affect simultaneously the lending and currency markets for most banks, making it difficult to find a control group. In this paper, I address this concern because, given that not all banks can arbitrage in the same degree, I can compare the changes in bank lending of those banks that can arbitrage more these deviations relative to those that cannot arbitrage as much. A third challenge is that as the changes in aggregate economic conditions can also affect firms' investment opportunities as well as riskiness, it is important to isolate changes in banks' credit supply caused by changes in CIP deviation from changes in credit demand or changes in the riskiness of the firm. I address this challenge by using a within firm-month analysis. That is, given that 70% of firms in my sample have multiple bank relationships, I can compare how banks that have different abilities to arbitrage CIP deviations change their lending to the same firm on the same month.

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This paper is organized into five sections. The first two sections, which describe the setting and the data, provide context for the main section of the paper. The main section of the paper is Section IV. This section presents the methodology and results. Given that the conclusions of this paper are reached by following three steps, this section is divided into three subsections, with each describing the methodology and result for the respective step. Section V explores how the results could be affected by the correlation between the basis and the FX and firnds that the FX does not affect the results. Finally, Section VI concludes.

II. Setting: CIP deviations and the currency composition of bank lending

This Section provides background information on two main ingredients of this paper: CIP deviations and bank lending. On CIP deviations, Part A describes how CIP works and how arbitrage is done, while Part B takes CIP deviations to the data. On bank lending, Part C describes the setting and banks' balance sheets.

A. Review of CIP

CIP is a non-arbitrage condition that states that an investor should be indifferent between two lending strategies. The first strategy is to lend directly in a particular currency, say soles (PEN).[11] This strategy is colored red in Figure 1. 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 strategy is highlighted in blue and refers to lending soles synthetically. This strategy starts by 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 $y^{\$}_{t,t+n}$. Hence, as of $t+n$, the investor will receive $\frac{1}{S_t} \times (1+y_{t,t+n})^n$. At time t, the investor also locks into a $t+n$ FX to convert the USD loan proceeds into PEN. This is done by using a forward contract[12], which exchanges PEN for USD at $t+n$ using an FX of $F_{t,t+n}$. Using the $F_{t,t+n}$ FX (also quoted as soles

[11] Soles is the Peruvian currency and has currency code PEN.

[12] FX forward contracts are contracts in which an investor commits to purchase a certain amount of a currency in a determined future date and FX.

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per dollars) to convert the dollar loan proceeds to PEN, gives 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 are 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 return of this second strategy as $y^{fwd}_{t,t+n}$. This is the soles synthetic rate (or forward-implied soles rate) and, 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: [13]

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

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: (1) borrowing soles (dollars) directly, (2) converting these soles (dollars) to dollars (soles), (3) lending in dollars (soles) while (4) 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 is left as profit, in terms of annualized return, is the cross-currency basis (in absolute terms).

B. CIP Deviations in Peru and Other Latin American Countries

What does the data show on the CIP deviations in Peru? Do they relate to CIP deviations in other Latin American economies? To study these, I use Equation (3) to compute the cross-

[13]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.II, this definition is equivalent to Equation (3).

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currency basis for various currency pairs. Panel A of Figure 2 plots the annualized cross-currency basis for 1-month contracts for the soles-dollar currency pair (USDPEN) and the average across other Latin American currency pairs between 2005 and 2013. 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. 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. Table I 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 (February 2005-2013, excluding the financial crisis). This is larger than in developed economies, where for example, the average absolute 1-month USDEUR basis has been 0.22% during the same sample period.[14] 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 table for Peruvian banks has been borrow the local currency synthetically and lend it directly.

C. Overview of the Peruvian banking system

This section describes two characteristics of the Peruvian banking system. First, it describes the partially dollarized setting in which banks operate. Second, it describes the composition of their balance sheets. In this paper, the former is important to understand the implications of the currency composition of bank lending. The latter is important to have a better understanding of

[14]Given that EURUSD, by convention is a quote of dollars per euro, I have reported the flipped version of USDEUR (euros per dollar) to make it comparable to quotes in Latin America. In Latin America, currencies quote as the amount of local currency per dollar.

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the frictions that could be at play regarding banks' internal capital markets, and therefore, the connection between arbitraging CIP deviations and bank lending.

Banks in Peru operate in a setting which is very common across emerging economies: a partially dollarized financial system.[15] This means that banks in Peru borrow and lend in both, dollars and soles. During the sample period, loan and deposit dollarization averaged 59 and 55%, respectively. Firms and households borrowing in dollars are not hedged. Indeed only a small fraction of firms are exporters or have hedging instruments. While dollar savings provides a natural hedge, and, in aggregate banks' dollar deposits closely match their dollar lending, there is significant heterogeneity in terms of *who* has net dollar assets and *who* has net dollar liabilities. Hence, the large share of bank dollarization means that local agents are highly exposed to the exchange rate. Therefore, changes in the currency composition of bank lending can play an important role in terms of shifting currency risk to local agents. Ultimately, as shown by various studies, this ends up having important effects on the real economy.[16]

A common characteristic of banking systems across the world is that this sector is composed by few banks. The 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 II, which reports summary statistics of the main sources of funding and lending for Peru's banking system for both soles and dollars.

Bank deposits play a crucial role in terms of enabling banks fund either their bank lending activities or their trading activities in both soles and dollars. Indeed, deposits represent 75% of the banking system's liabilities. Then, expanding one of the banks' business divisions, such as increasing trading activities, without affecting other ones, such as bank lending, very likely relies on banks' abilities to increase its deposit base.

[15] 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

[16] See Kim et al. (2015); Aguiar (2005); Verner and Gyöngyösi (2020).

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Yet, Table II suggests that banks might not be able to increase their deposit base easily. Within deposits, checkings and savings represent approximately half of the deposits. These deposits are likely to be very inelastic for two reasons. First, given these deposits are very liquid they have interest rates that are close to zero (less than 0.3% in either soles or dollars). At near zero rates, even doubling the interest rate would imply a very small rate and might not propel an important response on total deposits invested in the banking system. Second, households are the ones saving mostly with checkings and savings accounts. Relative to firms, they are also more likely to be less sensitive to rates as they might not be shopping for higher rates.

The type of deposits that could be more elastic and that therefore, could probably be increased at a faster rate to finance additional trading or lending activities are term deposits. These deposits cannot be withdrawn them before the maturity date and, on the bank side, are significantly more costly. For instance, although 85% of term deposits are less than one year, the average rate paid on term deposits has been 3.64% and 2.16% for soles and dollars respectively. These deposits constitute the other half of deposits and the deposit base is composed by mostly firms.[17]

Other sources from which can be easy to obtain funding but that are relatively very small markets (or only viable at specific times) are funding dollars from abroad and borrowing soles from the Peruvian Central Bank.[18] In both cases, these are subject to the discretion of the Central Bank: either capital controls on inflows when borrowing dollars from abroad, or auctions from the Central Bank of Peru when borrowing soles using repos.[19] [20]

[17]The bank regulator's website reports that approximately 70% of term deposits are from firms, 24% from households and the remaining 6% from non-profits.

[18]Both, borrowing from abroad from foreign banks as well as borrowing from the local financial system (including the Peruvian Central Bank) are reported as "obligations with the financial system" in banks' balance sheets (and therefore in Table II). The description of this balance sheet account is in the SBS website

[19]In the case of dollars, in a frictionless economy, banks would be able to borrow from abroad without restrictions. However, regulations such as capital controls on inflows has made it significantly more costly to borrow dollars from abroad. As these restrictions vary over time, the availability or cost of these funds is also time-dependent.

[20]The Central Bank of Peru uses repo auctions to lend in soles. These auctions occur seldomly and only when there is significant scarcity of soles funds. In the sample, this occurred twice. One in early 2006 that occurred due to the uncertainty due to an upcoming election. The second is during the financial crisis. There are other types of repos with the Central Bank that are always available and are called "direct repos". These repos, though in theory always available, they are barely used. Private conversations with banks reveals that there is a reputation cost tight to using this instrument (that can signal a bank is in distress) and therefore they avoid it at all costs.

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III. Aggregate, Bank-Level and Loan-Level Data

The sample period for all datasets I use in this paper begins in February 2005 and ends in February 2013. February 2005 is when one of the main datasets, the credit registry, begins. I chose February 2013 as the end date of the sample because, starting at the end of 2013 until at least the start of 2016, there are many confounders that are discussed in Appendix A.III.[21]

I combine many datasets. First, I use market-based data. I obtain 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 I. This table was analyzed in Part B of Section II.

Second, I use bank-level data combined from a series of individual bank reports to the bank regulator, SBS. These reports are, in its majority, confidential. They are all mandatory for all banks operating in Peru. The first report entails the universe of their forward contracts. The second report contains their daily spot transactions. I have corroborated these daily transactions are consistent with their reported forward and spot positions. The third report contains their daily positions on various money market accounts, such as their 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.

The summary statistics of banks' balance sheets and additional money market accounts are shown in Table II and was described in Part C of Section II. Panel A of Table III shows the summary statistics of additional non-balance sheet accounts, such as liquidity, profitability and FX derivatives. An important observation is that FX derivatives are an important component of banks' balance sheets, representing nearly 20% of their assets. Yet, 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. This table also has summary statistics of "net

[21] 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.

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matched position" and $\hat{\beta}$. "Net matched position" is the spot position that has been matched with the opposite transaction in the forward market. $\hat{\beta}$ is the estimated sensitivity of assets allocated to arbitraging CIP deviations after a 1pp increase in the cross-currency basis. "Net matched position" and the estimation of $\hat{\beta}$ are described in Part A of Section IV.

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, the main dataset used in this paper. The credit register is confidential. It contains the monthly balances of all commercial loans outstanding in dollars and soles to firms that have had at some point during the sample a loan outstanding of more than 300,000 soles (approximately 100,000 dollars) in aggregate with all the financial system.

There are almost 28,000 firms in the credit register. Panel B of Table III shows the summary statistics of these firms. Those labeled "small firms" are those with yearly sales that are below 20 million soles (6.5 million dollars approximately). The medium firms are those with yearly sales between 20 and 200 million soles (6.5 to 65 million dollars) and the large firms are those with yearly sales above 200 million soles.[22]

IV. Arbitraging CIP Deviations and Bank Lending: Methodology and Results

This section studies the effect of arbitraging CIP deviations on bank lending with a set of complementary empirical strategies. First, I analyze banks' money market and FX transactions to show that these transactions correspond to those required to arbitrage CIP deviations. However, I also show that banks have different "abilities" to arbitrage such deviations. Second, I show that banks face balance sheet constraints when arbitraging these deviations. From the internal capital market standpoint, this means banks have a trade-off regarding the use of their funding. Arbitraging CIP deviations would then entail using resources that otherwise would have been used to lend. Finally, I corroborate that this is indeed the case by studying how arbitraging CIP deviations affects lending. For each of these three steps I present the methodology and results.

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

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A. Step 1: Are banks arbitraging CIP deviations? Are there differences across banks?

I start by performing an aggregate level analysis to show that banks' transactions are consistent with attempts to arbitrage CIP deviations. To do so, I add the balance sheets of all banks in the sample and study the correlations between the cross-currency basis and the various balance sheet accounts that are directly involved in arbitraging the cross-currency basis. I show these correlations are statistically significant and have the expected signs.[23]

Next, I present the empirical specification used to test the correlation between balance sheet accounts and the basis. I allow the strength of these correlations to be asymmetric when the cross-currency basis is positive than when it is negative. This is because, building over Part A of Section II, arbitraging a positive basis requires banks to borrow soles (PEN), whereas it requires dollar (USD) borrowing when negative. Therefore, it is likely that an arbitrageur increases more its soles borrowing when the cross-currency basis is positive, as compared to when the basis is negative. To allow for such potential asymmetry, I estimate the following time-series regression:

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

where y_t is some balance sheet account as percentage of total assets, CCB_t is the USDPEN cross-currency basis and $\mathbf{1}(\cdot)$ is the indicator function. Thus, θ_1 and θ_2 capture the correlations between y_t and the basis when it is positive and when it is negative, respectively. As noted before, the USDPEN cross-currency basis is mostly negative in my sample, meaning that the estimation of $\hat{\theta}_1$ could be somewhat low-powered.

The dependent variables studied are those directly linked to arbitraging CIP deviations and can be split into three groups: borrowing, lending and FX transactions. To prevent the growth in these accounts due to balance sheet growth, all balance sheet accounts are scaled by total assets.

The results for the three groups of variables are presented in Panel A of Table V and they are all consistent with arbitraging CIP deviations. As the cross-currency basis increases, we see the following: From the borrowing side, arbitraging banks increase their borrowing in soles and

[23] Although the analysis in this part, Part A, is not causal, as I cannot rule out other potential confounders, it is an important building block for the next sections. More specifically, Part C will then exploit the bank-level variation to study how arbitraging CIP deviations affect bank lending.

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decrease their borrowing in dollars. From the FX side, banks buy more dollars spot and sell dollars forward. From the lending side, banks lend in dollars and lend less in soles.

Asymmetry is also present and in the expected direction. From the borrowing side, the coefficient associated with positive basis is larger and more significant for soles than its negative counterpart. The opposite (in absolute values) happens to dollars. From the spot side, the coefficients for buying dollars spot and selling dollars forward are stronger in absolute values when the basis is positive than when it is negative. From the lending side, investing in dollars is more stronger when the basis is positive than when it is negative. An interesting result is what happens with soles. In soles, the statistical significance comes when the basis is positive. The negative coefficient on soles shows that as the basis increases, banks divest in soles certificates of deposit of the Central Bank and sovereign debt. This is expected because when the basis increases and banks need to fund soles to arbitrage, these securities are often left to expire (the certificates of deposit are short term) or used as a pledge in repos. Therefore, these can be seen as a source of funding in soles.

An interesting result from this analysis is the magnitude of the coefficients that correspond to spot and forward transactions (Columns 5 and 6). In absolute terms, they are two to three times as large as those in the borrowing and lending sides. An increase in 1 pp increase in the cross-currency basis is associated with a 3.34 pp increase in the spot dollar long position when the basis is positive and 2.69 pp when it is negative. Given that these dollar spot purchases when the basis increases are more than twice as much than the soles borrowed to possibly arbitrage these deviations means that banks are only funding half of their dollar purchases with new soles borrowed with interbank loans and financial obligations (the analogous occurs with dollar borrowing when the basis decreases). Hence, 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).

To understand how these results change at the bank-level, I estimate the same regressions as I did at the aggregate level but at the bank-month level and including bank fixed effects. The results are shown in Panel B of Table V. In general, the results still hold but are less robust. This difference can be partially attributed to an important fact that was masked when aggregating data: not all banks' actions are consistent with arbitrage. This bank-level heterogeneity is very relevant, as it

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will be necessary for a clearer identification of the channel which affects bank lending which I propose in this paper.

To analyze further how banks differ in their "ability" to arbitrage CIP deviations, I look at the sensitivity of the share of the banks' assets likely used to fund arbitrage after a change in the cross-currency basis. This sensitivity, which I measure using bank-level regressions, requires a proxy for the share of a bank's assets invested in arbitraging the basis. Therefore, first I build this proxy and then I compute the bank-specific sensitives.

The proxy I use to capture the funds used to arbitrage CIP deviations is a daily measure of the forward + swap position of a bank that is matched with its spot position. I use this proxy because any arbitrage transaction requires banks to match their forward transactions with a transaction of the opposite side in the spot market.[24] For brevity, I refer to this measure as the matched position of a bank.

Formally, I define the matched position of a bank as follows:

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

In the first case, when Matched_{bt} is strictly positive, a bank has a net long dollar forward position (Fwd+Swap Pos.>0) and a net short dollar spot position (Spot Pos.<0). The Matched_{bt} is the amount of its long forward position that is effectively matched with its short spot positions. Consequently, Matched_{bt} is the minimum between the absolute value of the spot position and the forward position. This is precisely the type of strategy banks perform when they try to arbitrage CIP and the basis is negative. In this case, arbitrage requires selling dollars spot and buying dollars forward. In the second case, when Matched_{bt} is strictly negative, the converse happens and banks follow this strategy to arbitrage positive basis.[25] Finally, if a bank has the same (long or short)

[24] This required the spot and forward transactions of all banks in Peru, which banks submit in confidential reports to the bank regulator.

[25] 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

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dollar position in both the spot and forward markets, it is not hedging any risk nor matching the positions. Hence Matched_{bt} is zero.

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

$$\left(\frac{\text{Matched}}{\text{Assets}}\right)_{bt} = \alpha_b + \beta_b \text{CCB}_t + \varepsilon_{bt} \qquad \forall b \in B \tag{5}$$

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.

Notice that the way I have constructed Matched_{bt} implies that a bank that arbitrages CIP deviation will have a negative time-series correlation between Matched_{bt} and the USDPEN cross-currency basis. Therefore, if bank b arbitrages CIP deviations, we would expect to observe $\beta_b < 0$. Moreover, if bank 1 pursues a more aggressive arbitrage strategy than bank 2, we would observe $\beta_1 < \beta_2 < 0$. This means that bank 1 matches a higher percentage of its assets in the direction predicted by arbitrage when the basis changes by 1 pp. So, I will interpret the estimated $\hat{\beta}_b$ coefficient as proxy of bank b's intensity of arbitrage capabilities/activities.

Why use the matched position of a bank instead of other accounts as proxy for arbitrage activity? Relying on the use of the FX market is a cleaner proxy than the bank's use of the money market. It is difficult to pick a set of money market accounts as a measure of arbitrage activity that is valid across banks and through time. For example, divesting liquid soles assets can be equivalent to borrowing soles at a very low rate (see Column 7 of Table V). So, if a bank wants to arbitrage CIP it can perform any of these two actions, depending on i) borrowing constraints and ii) liquid assets availability, which 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

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.

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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 V.

Estimating equation (5) 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. As can be seen, there is a concentration of banks with 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 [-3.4,-0.8], respectively.

I verify that $\hat{\beta}$s are effective at capturing arbitrage ability. To show this, I split banks into low and high-arbitrage banks and use these two groups of banks to estimate the same regressions of Panel B in Table V for each group. As one would expect, I show that the estimated coefficients for the arbitrage accounts are larger in the group of high-arbitrage banks, than in the low-arbitrage one. These results are shown in Panels C and D of Table V. 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. On the other hand, 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. This is evidence for the fact that using the $\hat{\beta}$s based on the matched position of a bank as a proxy for its arbitrage activity is a good way of separating the sample in this dimension.

B. Step 2: Does it seem banks face constraints when funding their arbitrage transactions?

The opportunity to arbitrage CIP deviations creates a risk-free marginal profit. However, to engage in this arbitrage, banks need funding in a particular currency.

When banks are not constrained, banks do not face a trade-off on where to invest the marginal currency. Banks can simply tap in their liquid funding sources until the marginal profit of both arbitrage and lending is zero. However, when banks are constrained, their decision to invest

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depends on the marginal return of the competing business lines.[26] Revealed preference (i.e. the results in Part A) shows that banks prefer to allocate part of their funds to arbitraging CIP deviations.

Arbitraging CIP deviations under a constrained scenario likely leads to less lending in the currency required to do the arbitrage. As an example, consider that the cross-currency basis is negative (positive). Arbitraging these deviations requires borrowing in dollars (soles). Banks can source funds internally or externally. On one hand, if banks choose to source funds internally, they will be reallocating dollar (soles) resources away from its lending division in order to arbitrage CIP deviations. Such shift in resources consequently leads to a decrease in dollar (soles) lending and is probably the most direct way how arbitraging CIP deviations affects the lending division of banks. On the other hand, if banks source externally, they will need to pay more for dollar (soles) deposits. Assuming banks increase their dollar lending rates to account for their higher marginal cost, firms will have incentives to substitute their dollar (soles) borrowing for soles (dollar) borrowing. Hence, the equilibrium outcome would be a reduction in dollars (soles) bank lending and possibly an increase in soles (dollar) bank lending.

Next, I show aggregate and bank-level evidence that under CIP deviations, liquidity becomes scarcer or more expensive in the currency needed to do the arbitrage.

To proxy for liquidity, I use two sets of variables. First, I use are interest rate spreads over the monetary policy target rate.[27] I interpret an increase in the rate spreads as an increasingly binding liquidity constraint for the bank. This is intuitive, as it means that the bank has to pay increasing funding rates in order to enlarge its balance sheet. I compute this spread for two sources of financing that are likely used for arbitrage: new term deposits and interbank loans.

Second, I use are the share of liquid assets in soles and dollars. 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. Notice that a

[26] This is equivalent to a constrained optimization problem, where there is a borrowing constraint on liquidity. For a trade-off to exist, the Lagrange multiplier of the borrowing constraint must be positive.

[27] I focus on spreads rather than on interest rates to consider banks' account for changes in monetary policy. For soles rates, I use spread with respect to the Peruvian Central Bank's target rate. For dollar rates, I use the spread with respect to the Fed's target rate. Using the spread with respect to libor yields very similar results.

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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. Therefore, liquid assets in dollars increase while liquid assets in soles decrease, making the share of liquid assets in dollars increase and soles decrease.[28]

The correlations between the basis and the proxies for liquidity suggest that the currency banks need to borrow to arbitrage CIP deviations is scarce. This is shown in Panel A of Table VI, which replicates the analysis of Equation 3 using as dependent variables the interest rate spreads and the shares of liquid assets for the aggregate banking system. To interpret the results, recall that when the cross-currency basis increases, banks need to borrow soles to arbitrage. Columns 1 and 3 show that precisely when banks require liquidity in soles (PEN) to arbitrage, the soles term deposits and soles interbank loans become more expensive. This is also when the share of soles liquid assets decrease (Column 5). [29] On the contrary, when the basis decreases, arbitraging CIP deviations require banks to borrow dollars. This is precisely when spreads on dollar term deposits and interbank loans increase (Columns 2 and 4).[30] It is also when the share of dollar liquid assets decreases (Column 6).

What causes this increase in spreads? Although a possible explanation is exactly the demand of funds to arbitrage CIP deviations, the results shown here are correlations. Hence, by no means I claim causality. Given that CIP deviations correlate with other macroeconomic factors, I do not intend to argue CIP deviations cause the increase in rates. Indeed, Section V explores a different factor correlated with CIP deviations that is also likely to be an important contributor to the increase in rates.

[28]Notice that although total assets (the denominator) in dollars increase and in soles decrease the proportional change in the numerator is larger, making the change in the numerator determine the direction of the change.

[29]A 1pp increase in the cross-currency basis is associated with an increase of 0.3pp in the soles term deposit spread. In terms of soles interbank rates, the spread is significantly smaller. It is also the only result regarding spreads that is not statistically significant. A possibility for this is that banks use repos and certificates of deposit of the Central Bank to manage soles liquidity.

[30]A 1pp decrease in the cross-currency basis is associated with an increase between 0.4 and 0.6pp in the dollar term deposit and interbank spread.

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However, importantly, for this paper, it is not important where the scarcity of liquidity comes from. What is important 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 way, as previously described, this can impact bank lending and this is what is going to be tested in the next section, Part C, Section IV.

Finally, as I did in the previous section for robustness, I estimate the same aggregate regressions, but at the bank-month level and using bank fixed effects.[31] Panel B in Table V shows the results, which generally have the same signs and significance as in Panel A. As before, the bank-month level regressions can be estimated for the two subsamples of high- and low-arbitrage banks (Panels C and D). The estimated coefficients for the interest rate spreads are not very different between the two groups. This gives support to other explanations that are not related to CIP deviations, as it impacts all banks regardless of their arbitrage activities. On the other hand, one can notice that the liquidity ratios' coefficients are 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 is consistent with the previous hypothesis that it is indeed bank's arbitrage that is driving part of these liquidity changes.

C. Step 3: How does arbitraging CIP deviations affect bank lending in soles and dollars?

So far, the previous sections have shown that although banks seem to have constraints expanding their balance sheets to arbitrage CIP deviations, their transactions are consistent with them arbitraging these deviations (albeit partially). This section explores whether arbitraging CIP deviations in this context affects the currency in which banks decide to lend.

From an internal capital market standpoint, it is expected that banks that arbitrage more CIP deviations would shrink their lending in the currency that it needs to borrow to arbitrage these deviation. So as not to lose clients, these banks could also induce firms to swap their borrowing to a different currency. For example, as the cross-currency basis increases (decreases), arbitraging

[31] 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.

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CIP deviations entail borrowing soles (dollars) and hence, we could expect banks to substitute soles (dollar) lending for dollar (soles) lending.[32] While arbitraging CIP deviations technically involves lending in risk-free money market instruments, banks could in part decide to lend this to riskier firms in order to prevent from losing their market share in their lending division. Next I describe the methodology to test this hypothesis.

C.1. Methodology

There are three main methodological challenges when testing whether the previous hypothesis is validated in the data.

First, CIP deviations are a macroeconomic outcome. As such, they can correlate with other macroeconomic factors. This makes it important to search procedures to disentangle changes in bank lending that come because of CIP deviations from those coming from other macroeconomic variables that correlate with CIP deviations.

Second, the same changes in aggregate economic conditions that could be affecting CIP deviations can also affect firms' investment opportunities. Then, it is important to control for changes in credit that are due to changes on the firm side, such as credit demand.

Finally, banks in Peru might decide to lend in a particular but might not want be exposed to that currency. In that case, the bank could use forward contracts to hedge. However, unlike other types of investors that hedge in the USDPEN forward market, banks in Peru are market makers in this market. Then, their actions in the USDPEN forward market have significant effects on the prices of USDPEN forward contracts and, therefore, on the USDPEN cross-currency basis. Hence, ideally, one would like to have a setting in which banks cannot affect the cross-currency basis.

Taking these challenges into consideration, I estimate the following two-stage least squares model:

$$CCB_{t-1}^{\text{Peru}} \times \text{Arb.Intensity}_b = \gamma_0 + \gamma_1 \text{CCB}_{t-1}^{ChMex} \text{Arb.Intensity}_b + X'_{b,t-1}\Theta + \text{Bank FE} + \upsilon_{b,t-1} \quad \text{(6a)}$$

[32] Funding dollars (soles) in this example is not problematic because the arbitrage requires banks to switch the soles (dollars) the banks borrowed into dollars (soles) and lend in dollars (soles).

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$$y_{bft} = \alpha_0 + \alpha_1 \, \widehat{CCB^{\text{Peru}}_{t-1} \times \text{Arb.Intensity}_b} + \text{Bank} \times \text{Firm FE} + \text{Firm} \times \text{Month FE} + X'_{b,t-1}\Psi + \varepsilon_{bft} \tag{6b}$$

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; CCB^{Peru}_{t-1} is the 1-month lagged cross-currency basis of USDPEN; CCB^{ChMex}_{t-1} is the average 1-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 A and measures the bank arbitrage intensity level[33]; $X_{b,t-1}$ is a vector of 1-month lagged bank controls; *Bank* $\times$ *Firm FE* and *Firm* $\times$ *Month FE* refer to bank-firm fixed effects and firm-month fixed effects, respectively. Equations (6a) and (6b) refer to the first and second stage of the two-stage least square model, respectively. The estimation sample is between February 2005 and February 2013 but excluding the financial crisis (December 2007 to July 2009)[34] to prevent the results from being driven by outliers from this period.

In this regression, the coefficient of interest is α_1. It measures the percentage increase in bank lending of increasing arbitrage intensity by 1 (i.e increasing -$\hat{\beta}$ by 1) after a 1 percentage point increase in the cross currency basis when lending to the same firm on the same month. Then $\hat{\alpha}_1$ simultaneously compares (1) the lending of the *same bank* to *the same firm* at different levels of CIP deviations and (2) the lending of high arbitrage-intensive banks relative to less arbitrage-intensive ones. Given that the USDPEN cross-currency is instrumented with the average of Chile and Mexico's currencies against the dollar, the results are only driven by changes in the cross-currency basis that arise from external shocks that are very unlikely to be affected by actions of banks in Peru.

This baseline specification already alleviates some of the concerns previously mentioned. I will specify the remaining concerns and the steps I use to mitigate these after presenting the baseline results.

First, the baseline regression mitigates some endogeneity concerns. It does this in two ways. First, it does not focus on CIP deviations themselves, bur rather on the link between *arbitraging* CIP

[33] 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.

[34] These dates are the dates used at the NBER to indicate recession during this period.

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deviations and bank lending. Given that arbitraging CIP deviations involve a set of transaction, studying the link between these specific set of transactions and bank lending makes it more likely to capture the link to CIP deviations. Second, the way that the regression studies whether arbitraging CIP deviations affect bank lending also helps isolate the channel of CIP deviations. By using variation at the bank-level on their arbitrage-intensity (measured by $-\hat{\beta}_b$), it compares bank lending across banks with different arbitrage intensities. Therefore, common macroeconomic shocks that affect all banks equally at the same time are "differenced away".

Note, however, that when shocks do not affect all banks in the same way, these will not be fully "differenced away" and could lead us to mistakenly attribute changes in bank lending to arbitraging CIP deviations. For example, consider a macroeconomic shock that, although it is unrelated to the cross-currency basis, is correlated with it. For illustration, assume that the cross-currency basis increases. At the same time, assume that this shock also affects more the more-arbitrage intensive banks (those with highest $\hat{\beta}$ in absolute terms) and simultaneously also makes soles lending to decrease. Then, one could mistakenly conclude that when banks arbitrage an increase in the cross-currency basis, they lend less in soles (as expected from an internal capital market standpoint).

In this regression, I add bank fixed effects (embedded in bank-firm fixed effects) and bank time-varying controls to mitigate the concerns regarding alternative shocks not affecting banks in the same degree.

However, the controls and bank fixed effects might not be sufficient to rule out that the results are driven by the heterogeneity across banks. This is particularly the case because: (1) banks are heterogeneous and (2) we know that the cross-currency basis can be correlated with other factors that could affect banks differently. I address the first concern later in this section and the second concern in Section V. In sum, I show that the results are robust to narrowing the sample to very similar banks and that important possible confounders do not seem to explain the results.

Second, the specification in Equation (6b) addresses the concern related to changes in aggregate economic conditions affecting firms' investment opportunities by including firm-month fixed effects. Using firm-month fixed effects keeps only firms with multiple bank relationships (more than 70% of my sample) and compares how banks with different arbitrage intensities change their lending to the *same* firm and month. Under the assumption that when firms want to borrow funds,

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they ask for quotes to all the banks with which they have a relationship with and take the lowest quote, adding firm-month fixed effects would absorb possible changes in firms' credit demand and allow the main coefficient of interest, α_1, to capture only credit supply.

However, when this assumption does not hold, and firms have a preference for a particular bank, they might only ask for a loan to that particular bank and not ask for a quote to all banks with whom it has a relationship with. This could be problematic because when firms have a preference, $\hat{\alpha}_1$ could be picking up the preference to borrow from a particular bank rather than the changes in credit supply due to banks arbitraging CIP deviations.

Equation (6b) mitigates the concern that the results are driven by a particular preference of a firm to borrow from a particular bank by adding bank-firm fixed effects.

Finally, the two-stage least squares setup alleviates the endogeneity concerns regarding banks' capacities to simultaneously alter the USDPEN cross-currency basis (via their USDPEN forward transactions) and bank lending. The idea of instrumenting the USDPEN cross-currency basis with the cross-currency basis of countries is that the instrumented cross-currency basis of Peru is exogenous to the transactions of Peruvian banks.

For the instrument to be valid, two conditions should hold. First, instrument should only affect bank lending in Peru through its correlation with the USDPEN cross-currency basis. Although this assumption is untestable, this is likely to be the case because significant part of the variation of USDPEN cross-currency basis seems to be driven by global conditions that are exogenous to the Peruvian economy. Second, the instrument should be highly correlated with the USDPEN cross-currency basis so as not to suffer from a weak instrument problem.

With these considerations in mind, I instrument the USDPEN cross-currency basis with the average of USDCLP and USDMXN because of two reasons. The first reason for using these currencies is that these are the two currencies in Latin America with strongest correlation with USDPEN. As shown in Table I, the average basis of USDCLP and USDMXN has a correlation of 0.51 with the USDPEN cross-currency basis. This is a first signal that the instrument might not suffer from a weak instrument problem. The next section presents the first-stage results suggesting that indeed there is not a weak instrument problem. The second reason for choosing this instrument is that

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Peruvian banks barely trade these currencies and hence, are unlikely to affect their prices. Using the dataset that includes all forward transactions of banks in Peru, I confirm that during my sample period, less than 1.1% of all of the forward contracts that banks in Peru traded were USDMXN or USDCLP.[35] Therefore, it is very unlikely that Peruvian banks are price setters of USDCLP or USDMXN and hence, that they can affect the cross-currency basis in these currencies.

The potential bias that not instrumenting the USDPEN cross-currency basis with that of other countries is likely a negative bias. This makes the effects on bank lending seem lower than they actually are. This is because when a bank considers lending in a particular currency and as part of that lending decision, also use forward contracts, it is likely related to a decision to hedge changes in that currency exposure. As an example, consider a bank that decides to lend in soles. When the bank does not want to be exposed to changes in the value of the soles, it would also hedge these soles in the forward market by buying dollars forward. Given that the bank is a price maker, it has an obligation to quote bid and ask prices on forward contracts to its customers. However, as a way to increase its dollar forward position, the bank could increase its USDPEN forward quote on USDPEN, which effectively means reducing its supply of hedging against soles. If the bank is large enough, this effect can increase the cross-currency basis. Therefore, an increase in soles lending would be paired with an increase in the cross-currency basis. When this happens, it can go against the channel proposed in this section, where an increase in the cross-currency basis decreases soles lending and increases dollar lending. Therefore, this scenario can bias downwards absolute value of the coefficient on the effect of arbitraging CIP deviations on bank lending.

Although the baseline regression specification addresses various concerns, I perform various other robustness checks after presenting the baseline results. These checks include using alternative specifications and checks on the standard errors.

C.2. Results and Robustness

The main takeaway of estimating the baseline regression is that the estimates for all currency decomposition of loans (the different dependent variables) are consistent with the hypothesis proposed at the beginning of Section C. That is, an increase in the cross-currency basis increases

[35] Included here are also trades between MXN and CLP against PEN.

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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 35% and increase lending in dollars by 22%. In net, this represents a change in the currency denomination of the loans but not a change in the total loans.

Table VII 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 suggests that the it does not suffer from a weak instrument problem.

Table VIII 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 VII.

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.[36] Unless the bank borrows and lends in the same currency, the bank will need to hedge by selling dollars forward. As market maker, when the bank sells dollars forward, it will set downward pressure to the forward outright ($F_{t,t+n}$ in Equation 1) and decrease the cross-currency basis. This ultimately leads to lower cross-currency basis, higher dollar lending and lower soles lending (if lending more in dollars means banks prefer to lend less in soles); and hence, goes against finding a result through the mechanism proposed in this paper. Then, as expected, OLS estimates are significantly lower than the IV estimates.

Can differences in bank characteristics explain the results?

Although this cannot be tested, Table IX suggests that differences in bank characteristics do not seem to play a role in explaining the baseline results. This table shows the baseline regression results using only the subsample of the largest four banks. Relative to the baseline regressions

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

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using all banks, the results are even stronger when focusing on the largest banks for all variables. The largest differences with respect to Table VIII comes from a larger coefficient on dollar lending (increases from 22.6% to 44.6%) after an increase of 1pp in the cross-currency basis. This leads to an increase in total lending 9%. This result was only 3% with the baseline sample and was not statistically significant (now significant at 1%).

Related to whether bank characteristics can explain the results, I also provide robustness checks that suggest that if something, bank heterogeneity works against finding these results. Table XII shows alternative specifications, which include dropping bank controls and adding fixed effects one-by-one. Dropping all time-varying bank controls - which include measures of soles and dollar deposits, total assets, profitability and liquidity - yields very similar results to the baseline model. This provides further evidence that suggests that the possible heterogeneity across banks along differences in deposits, liquidity and profitability is not responsible for the results. Moreover, adding bank fixed effects even strengthens the results. For instance, starting from a specification with only firm fixed effects to one with bank and firm fixed effects does not affect much the coefficient of soles loans (which is close to -50%) but increases dollar lending by nearly 10% and strengthens its statistical significance to a level of 1%.

Table XII 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. This table shows five alternative specifications and they all show the same signs as the baseline regression and statistical significance. Dropping all fixed effects and controls shows that the magnitude, sign and statistical significance of the second-stage baseline results are almost unchanged. Starting from a plain regression and adding fixed effects one-by-one shows that the coefficient on the soles loan remains very stable. The same occurs for the share of dollar loans. The unambiguously increase in the share of dollar loans suggests that as the cross-currency basis increases and banks arbitrage these deviations, banks increase their share of dollar lending to firms.

Can credit demand and firm characteristics explain the results? I do not find evidence that credit demand of firm characteristics can explain the results. 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 take the same procedure as Gutiérrez et al. (2020), who

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also use the credit register from Peru, and narrow the sample to the most common type of loan, "prestamos", which are "commercial loans".[37] These constitute 50% of the loans given to firms in Peru. I show that the baseline results are even strengthened by this modification, as 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.

Finally, 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, just as what happens with 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 XI 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.

V. The Role of FX

An important assumption of the results presented in Section IV is that there is not a different factor that happens to affect more the banks that arbitrage more at the time there are CIP deviations that can end up explaining the results. Although I have used bank fixed effects, various bank controls when studying the effect of arbitraging CIP deviations on bank lending, as well as narrowed the analysis to very similar banks, the fact that CIP deviations themselves are endogeneous means that one could worry that there are other factors playing a role.

Indeed, the magnitude and correlation of CIP deviations across countries that was shown in Part B, Section II, suggests that there can be macroeconomic shocks that are affecting CIP deviations across countries.

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

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One important macroeconomic shock that affects CIP deviations across countries is the value of the dollar (i.e. the FX).[38] In the case of emerging markets, Figure 3 shows that value of the dollar is correlated with the cross-currency basis in Latin America.

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. In the sample period studied, however, the PEN has appreciated approximately 3% per year relative to the USD as the Peruvian economy has been performing very well.

How can the correlation between the USDPEN and the basis affect the results? Using as instrument the CIP deviations of other countries should significantly alleviate concerns. Therefore, we should expect that the results still hold. Yet, out of caution, in this section I study how this correlation affects the results in Section IV.

If the IV does not properly isolate the FX shocks, the positive correlation is a possible confounder when studying bank lending and trying to assess the role played by cross-currency basis itself. Through independent channels, both, a depreciation of the local currency and an increase in the cross-currency basis can 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. Going forward, I refer to this channel as the FX channel. The increase in the cross-currency basis means banks will want to arbitrage. To do so, banks borrow soles to switch them to dollars. Consequently, from both, the depreciation and increase in the basis, we can expect banks to increase dollar lending and shrink soles lending so as to mirror what is occurring to their funding side.

The net effect on credit is uncertain, however. The FX also affects credit demand. From the demand side, unless rates adjust so as to eliminate possible gains from depreciation, households and firms will likely demand more soles loans and less dollar loans when they consider the currency will continue depreciating.

[38] Avdjiev et al. (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.

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Next I discuss the actual implications of the correlation with the FX for the results presented in Section IV.

A. Implications for arbitraging CIP deviations (Part A of Section IV)

Arbitraging CIP deviations involved three group of transactions: borrowing, lending and FX transactions.

How does the correlation with the FX affect these transactions? First, from the borrowing side, if the only channel present was the FX channel, we would expect that banks' deposits in soles decrease and in dollars increase as the sol depreciates (and basis increases). This is opposite to what the channel of arbitraging CIP deviations suggests.

Appendix Table V shows that the channel of arbitraging CIP deviations predominates. However, this is because households and firms do not participate in interbank loans and financial obligations.

When we analyze bank deposits, where households and firms are present, we see that the FX channel dominates. Table A.III in the Appendix shows this. An increase in 1pp in the basis is associated with a decrease of 2.1 pp in soles and an increase of 2.6 pp in dollar deposits as share of total assets (Columns 1 and 2). Decomposing the correlation between deposits and the cross-currency basis by including the log of the FX in the regression shows that such signs were due to the positive association between the basis and the FX. After controlling for the FX, the coefficients associated with the cross-currency basis are not significant and fairly small (Columns 3 and 4).[39]

Given the opposing forces that explain the share of soles and dollar deposits, one would expect that banks that arbitrage CIP deviations would then face a *lower* reduction in the share of soles deposits and a *lower* increase in the share of dollar deposits as the channel of arbitraging CIP counteracts partially the FX channel. This is seen in Columns 5 and 6 of Appendix Table A.III where, as expected, the coefficients associated to the cross-currency are dominated by the FX channels, but the coefficients of its interaction with the banks' $\hat{\beta}$s have the opposite signs. Furthermore, Columns 7 and 8 show that this "attenuation" effect can be explained by up to two mechanisms:

[39]Instrumenting Peru's basis with the average of Mexico and Chile yields stronger predictions. After controlling for the FX, a 1pp increase in the basis is now linked to a significant 2.0 pp increase in the share of soles deposits and a 1.5 pp decrease in dollar deposits.

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i) CIP arbitrage counteracting the FX channel (mainly for PEN) and ii) high-arbitrage banks being less impacted by the FX itself.

Second, from the perspective of FX transactions, as the basis increases and this correlates with a local currency depreciation, households and firms save more in dollars but want to borrow more soles and less dollars. From the bank perspective, if they wanted to satisfy the greater soles credit demand, they will be converting the greater dollar deposits into soles (to lend soles) by selling dollars in the spot market. Due to regulations that they need to hedge currency mismatches, banks would be required to buy dollars in the forward market. Selling dollars spot and buying them forward as the basis increases goes against is would go against arbitraging CIP deviations. Table V suggests that the channel of arbitraging CIP deviations dominates. Indeed, when controlling for the FX, the results on spot and forward transactions are very similar, both in magnitude and statistical significance.

Notice as well, that the spot transaction cannot be explained by banks' desire to buy dollars as the sol depreciates. This is because due to regulations, banks have minimum FX risk. This is seen directly in Table V as banks sell dollars in forward when the FX depreciates, cancelling out any gains obtained by buying dollars in the spot market.[40] [41]

Third, from the perspective of lending, the most direct accounts affected by households and firms' preferences is credit. As I show later, the results of bank lending are robust to the inclusion of the FX, which suggests that the instrument and the bank controls were enough to account for changes in the FX.

[40]Who are the banks' counterparties willing to do the opposite trade as the basis increases? Foreign investors are an important counterparty in the forward market. As they hold securities in soles (such as soles government bonds), they will likely hedge their soles exposure by buying dollars forward as the sol depreciates. Although this paper does not study the causes of CIP deviations in emerging markets, it is likely that the significant demand of foreign investors to buy dollars forward, combined with regulations and other frictions, cause the increase in the cross-currency basis and therefore the positive correlation with the FX. For this paper, the causes are not important. What is important is that the set of transactions that banks do to arbitrage CIP deviations impact bank lending. This paper is agnostic to whether the cross-currency basis was partly explained by changes in the FX.

[41]Those frictions include: (1) regulations such as capital controls, that limit how much banks can buy or sell forward contracts (see Keller (2019)); (2) that it is harder for foreign counterparties to trade in the spot market due to lack of soles cash; (3) that local banks can borrow soles from the Central Bank of Peru while foreigners cannot.

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B. Implications for funding constraints when funding arbitrage transactions (Part B of Section IV

How does the positive correlation between the cross-currency basis and the FX affect banks' liquidity? Given that soles deposits drop and dollar deposits rise as the basis increases due to the sol depreciation, the correlation with the FX will only tighten liquidity constraints overall.

To uncover the effects that this will have on banks' internal capital markets and the ultimate bank lending results presented in the baseline specification (and its modifications), we need to understand whether the changes in the FX will affect more the banks that arbitrage. This is unclear. From the deposit side, we know that the banks that arbitrage make efforts to retain soles deposits as the basis increases. If the additional soles retained would go to lend in soles, then banks that arbitrage more would not be reducing lending in soles by more than those that arbitrage less. However, if banks are using more than the soles deposits they retain to arbitrage CIP deviations, then they will be lending less in soles. The same if they are paying more to retain these deposits and then quote higher rates on the lending side for soles lending. The opposite happens in dollars.

Table A.VI in the Appendix shows the results of bank-level regressions of various indicators of scarcity of bank liquidity in soles and dollars after controlling for the heterogeneous effect that changes in the FX can have on banks with different arbitrage intensities. There are three takeaways from this table. First, although banks arbitrage more manage to retain more soles deposits, they also end up paying more for them. Second, it does not seem bank deposits help in terms of liquidity. Indeed, liquidity ratio in soles (dollars) decreases for banks that arbitrage more as the basis increases (decreases). Given that liquidity ratios in dollars and soles are negatively correlated, this result, coupled with the results that show that banks arbitrage CIP deviations, it is likely that these funds are being used to arbitrage CIP deviations.

C. Implications for arbitraging CIP deviations and bank lending (Part C of Section IV)

An important concern regarding the estimated coefficient of the effect of arbitraging CIP deviations on bank lending is that it could be capturing the effects of changes in the FX rather than the effect of banks arbitraging CIP deviations.

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Given that the baseline regression estimates the *differential* effect of banks that allocate on average 1pp more of assets to arbitraging CIP on bank lending, if banks that on average allocate more to arbitraging CIP deviations are also the ones that are more affected by the FX, then the results could be overstated. Although the baseline regression controls for each bank's deposits in soles and dollars over time (as a share of assets), in case this control is not controlling fully for the effects of the FX, then the coefficient could be biased by the FX channel. That is, through the FX channel, we know that households and firms will be switching deposits from soles to dollars as the sol depreciates and this scarcity of soles funding, which happens at the same time that the basis increases, could induce banks to lend less soles and more dollars. Then, if the banks that arbitrage more are also those for which households and firms also switch more their deposits from soles to dollars when the sol depreciates, then these banks could have less liquidity in soles than banks that arbitrage less because of the FX channel. The relative decrease in liquidity through the FX channel that could affect more banks that arbitrage could then explain the results. However, I show this is not the case. Indeed, banks that arbitrage more are not the ones that are most affected by changes in the FX.

To show that banks that arbitrage the most are not the ones that are most affected by the FX, I compute the bank-level sensitivity of bank deposits after changes in the FX and contrast it to the bank-level arbitrage intensity. I use the sensitivity on bank deposits as 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:

$$\left(\frac{\text{Deposits}}{\text{Assets}}\right)_{bt} = \alpha_b^0 + \alpha_b^1 \log(\text{FX})_t + \varepsilon_{bt} \qquad \forall b \in B \tag{7}$$

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

Table A.V in the Appendix 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 the ones for which dollar deposits increase the most when the sol depreciates, while the banks in the low-range of arbitrage intensity are the ones that observe the greatest reduction in

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soles deposits as the sol depreciates. Therefore, the greater reduction in soles bank lending coming from banks that arbitrage more after an increase in the cross-currency basis cannot come 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 the ones that see 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 explaining the bank lending results by adding the interaction between arbitrage intensity (-β) and log(FX). The results are displayed in Appendix Table A.V.

VI. Conclusion

In this paper, I propose 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, they will attempt to arbitrage them when they can. To do so, they need to borrow in a particular currency. When banks cannot easily expand their balance sheets to fund this additional borrowing required to arbitrage CIP deviations, they can tap funds from their bank lending division and effectively decrease their lending in the currency required to perform the arbitrage. However, given that the arbitrage involves borrowing in a particular currency to lend in a different one, banks could be substituting lending in a currency for another rather than just decreasing the total quantity lent.

I test this proposed mechanism in three steps. First, I study whether banks' transactions suggest that they are arbitraging CIP deviations. I show this is the case. Interestingly, I also find that not all banks have the same "ability" to arbitrage these deviations. Second, I study whether banks can easily expand their balance sheets to fund their arbitrage transactions. I find evidence that suggests that banks experience difficulties in increasing borrowing to fund their arbitrage transactions. Finally, I study whether arbitraging CIP deviations ends up affecting bank lending. To do this, I use the finding of the first step, namely, that banks have different "abilities" to arbitrage CIP deviations, to show 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

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their lending in soles by 35% and increase their lending in dollars by 22% 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 argue that arbitraging CIP deviations can lead to changes in real outcomes by changing the currency composition of bank lending.

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Table I: Summary Statistics of CIP Deviations and FX Changes

This table shows descriptive statistics of the monthly time series of the 1-month cross-currency basis (CCB) for three groups of currencies between February 2005 and February 2013, 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 the correlation between the 1-year FX changes and the CCB.

	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	
Δ_{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	
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	
Δ_{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	
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	
Δ_{12m} FX (%)	-4.81	6.77	-22.00	9.07	77.00	0.30

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Table II: 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 III: 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 5 in Part A from Section IV. "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 IV, Part B.

	Mean	Median	SD	P5	P95	N
Panel A. Bank-Level Data: Balance Sheet, Liquidity, Profitability and FX						
Balance Sheet						
Assets (Billion USD)	4.15	1.41	6.14	0.21	18.49	887
USD Deposits / Assets (%)	32.91	34.27	15.13	4.81	53.86	887
PEN Deposits / Assets (%)	35.48	32.91	12.90	18.32	61.14	887
USD Credit/ Assets (%)	27.93	31.04	13.45	1.14	49.07	887
PEN Credit/ Assets (%)	34.22	26.65	19.60	11.59	72.66	887
Liquidity and Profitability						
Liquid Assets/ Total Assets (%)	27.26	25.75	11.37	12.81	49.12	886
PEN Liquid Assets / Total Assets (%)	12.88	11.35	7.56	4.54	27.86	886
USD Liquid Assets / Total Assets (%)	14.38	14.93	7.46	2.12	25.61	886
ROA (EOY, %)	1.84	1.80	1.79	-1.58	5.11	71
FX Derivatives and $\hat{\beta}$						
$\hat{\beta}$	-1.10	-0.93	1.18	-3.33	0.00	887
FX Derivatives/ Assets (%)	19.07	7.79	29.81	0.00	83.21	887
Net Matched Position (Million USD)	6.04	0.00	138.55	-216.19	219.85	887
|Net Matched Position| (Million USD)	73.02	11.16	117.88	0.00	320.87	887
Net Matched Position / Assets (%)	0.92	0.00	4.68	-4.77	9.34	887
|Net Matched Position|/ Assets (%)	2.34	0.43	4.16	0.00	11.49	887
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	767,709
USD Credit (Th. USD, Cons FX)	977.54	121.45	6,161.71	0.00	3,143.20	767,709
Total Credit (Th. USD, Cons FX)	1,351.72	193.24	7,356.26	9.55	4,494.72	767,709
Number of bank relationships	2.15	2.00	1.28	1.00	5.00	767,709
Panel C. Firm-Bank Level Data						
Credit By Firm per Bank						
PEN Credit (Th. USD, Cons FX)	172.35	0.73	1,625.63	0.00	414.85	1,666,691
USD Credit (Th. USD, Cons FX)	450.27	45.99	3,017.47	0.00	1,518.01	1,666,691
Total Credit (Th. USD, Cons FX)	622.63	91.48	3,508.71	0.99	2,157.01	1,666,691

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Table IV: 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 no arbitrage much. These have $-\hat{\beta}$ between 0 and 0.1. These also are the smallest group of banks. The second group, arbitrages significantly more ($0.1 \leq \hat{\beta} \leq 2$) 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 $\hat{\beta}$		
	$0 \leq \hat{\beta} < 0.1$			$0.1 \leq \hat{\beta} < 2$			$2 < \hat{\beta}$			$0 \leq \hat{\beta} < 1$			$1 \leq \hat{\beta}$		
	N	Mean	Sd	N	Mean	Sd	N	Mean	Sd	N	Mean	Sd	N	Mean	Sd
$\hat{\beta}$	400	-0.04	0.03	231	-1.11	0.24	256	-2.75	0.48	154	-0.94	0.02	154	-1.94	0.49
Net Matched Position (Million USD)	400	0.52	3.22	231	18.15	207.54	256	3.74	166.26	154	-8.01	232.71	154	-12.91	220.65
|Net Matched Position (Million USD)|	400	1.32	2.98	231	152.29	141.82	256	113.52	121.33	154	177.52	150.00	154	163.44	148.21
|Net Matched Position|$/Assets(\%)$	400	0.21	0.70	231	1.98	1.69	256	5.97	6.02	154	1.91	1.68	154	2.65	2.65
Total Assets (Bill. USD)	400	0.88	0.60	231	10.06	7.74	256	3.93	5.28	154	12.61	8.19	154	7.84	4.99
ROA (%)	32	2.38	1.86	18	2.17	0.55	21	0.74	1.93	12	2.07	0.61	12	2.51	0.33
PEN Liq. (% Assets)	400	9.81	4.20	231	12.36	4.26	255	18.19	10.56	154	13.45	4.45	154	12.29	4.13
USD Liq. (% Assets)	400	9.16	5.60	231	17.38	4.04	255	19.85	6.96	154	17.74	4.37	154	16.85	3.47
PEN Cred. (% Assets)	400	47.88	20.93	231	22.63	7.00	256	23.34	8.48	154	19.62	5.52	154	27.39	6.66
USD Cred. (% Assets)	400	22.21	16.63	231	33.75	3.79	256	31.61	9.32	154	35.30	2.32	154	33.09	4.91
PEN Dep. (% Assets)	400	42.99	13.93	231	29.86	4.06	256	28.81	9.88	154	28.60	4.11	154	33.26	3.49
USD Dep. (% Assets)	400	23.97	15.94	231	40.69	9.05	256	39.87	9.76	154	42.02	9.19	154	38.42	8.65

Table V: 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

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Table VI: 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

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Table VII: 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 (6a). 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 6a). 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)
$\text{CCB}_{t-1}^{\text{Chile,Mex}} * (-\hat{\beta})$	0.780***	0.593***	0.594***
	(5.08)	(4.30)	(4.49)
Bank Controls	No	No	Yes
Bank FE	No	Yes	Yes
F	25.85	18.46	20.15
Observations	1035629	1035629	1035629

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Table VIII: 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 6b. 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
$\text{CCB}_{t-1}^{\text{Peru}} * (-\hat{\beta})$	-8.389***	3.746**	0.161	0.442***	-35.37***	22.60***	3.195	2.123***
	(-2.77)	(2.21)	(0.29)	(2.67)	(-3.41)	(3.34)	(1.58)	(3.37)
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	1306168	1306168	1306168	1306168	1306168	1306168	1306168	1306168
N Firm Cluster	18185	18185	18185	18185	18185	18185	18185	18185
N Bank Cluster	77	77	77	77	77	77	77	77
Adjusted R2	0.747	0.809	0.724	0.818	-0.00275	-0.000650	0.00186	-0.00279

Table IX: 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 6b. 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
$\text{CCB}_{t-1}^{\text{Peru}} * (-\hat{\beta})$	-11.77***	8.320**	1.291	0.834***	-40.64***	44.59***	9.200***	3.511***
	(-3.04)	(2.41)	(1.13)	(3.04)	(-3.15)	(4.01)	(2.98)	(3.72)
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 Bank 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	-0.00	0.00	-0.01

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Table X: 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 $\text{CCB}^{Peru}_{t-1} * (-\hat{\beta})$ from the previous tables. The first row shows the baseline second-stage regression shown in Table VIII. 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	-35.37***	22.60***	3.19	2.12***
	(-3.41)	(3.34)	(1.58)	(3.37)
Baseline w/o Controls	-38.81***	17.82***	0.75	2.04***
	(-3.56)	(3.08)	(0.42)	(3.36)
No FE, No Controls	-56.91***	37.89***	-8.85***	4.31***
	(-3.92)	(2.91)	(-2.65)	(3.61)
Firm FE, No Controls	-51.49***	6.38	-16.91***	2.61***
	(-4.59)	(1.41)	(-3.82)	(4.70)
Firm FE, Bank FE, No Controls	-49.82***	15.19***	-10.99***	2.93***
	(-4.13)	(3.38)	(-2.93)	(4.53)
Firm FE, BankFE, Date FE, No Controls	-39.11***	19.63***	2.37	2.12***
	(-4.00)	(3.69)	(1.25)	(4.01)

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Table XI: 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	-35.37	22.60	3.19	2.12
Standard Errors:				
Baseline	10.36***	6.77***	2.02	0.63***
Bank Cluster	4.25***	13.07	4.28	0.68**
Bank and Date Cluster	8.59***	11.45*	3.53	0.72**
Firm Cluster	4.19***	3.74***	1.65*	0.27***
Firm and Bank Cluster	4.32***	10.82*	3.61	0.58***
Number of Clusters				
N. Bank Clusters	11.00	11.00	11.00	11.00
N. Date Clusters (N.Months)	77.00	77.00	77.00	77.00
N. Firm Clusters	18,185.00	18,185.00	18,185.00	18,185.00

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Table XII: Effect of Arbitraging CIP deviations on Bank Lending: Alternative "Arbitarge-Intensity" Measure

This table shows the second-stage results of a regression specification similar to the baseline regression but instead of using $-\hat{\beta}_b$ as a measure of arbitrage, it uses the 1-month lag of $-\frac{\text{Matched}}{\text{Assets}}$, where Matched is defined in Part A of Section IV. The first four columns show a specification without bank controls while the last show with bank 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
$\text{CCB}^{\text{Peru}}_{t-1} * \frac{-\text{Matched}}{Assets}_{b,t-1}$	-6.331***	2.325*	0.563	0.330***	-8.383***	1.025	-0.438	0.341***
	(-3.26)	(1.90)	(1.18)	(2.95)	(-3.49)	(0.85)	(-0.93)	(2.76)
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	1,325,383	1,325,383	1,325,383	1,325,383	1,325,383	1,325,383	1,325,383	1,325,383
F Stage 1	29	29	29	29	25	25	25	25

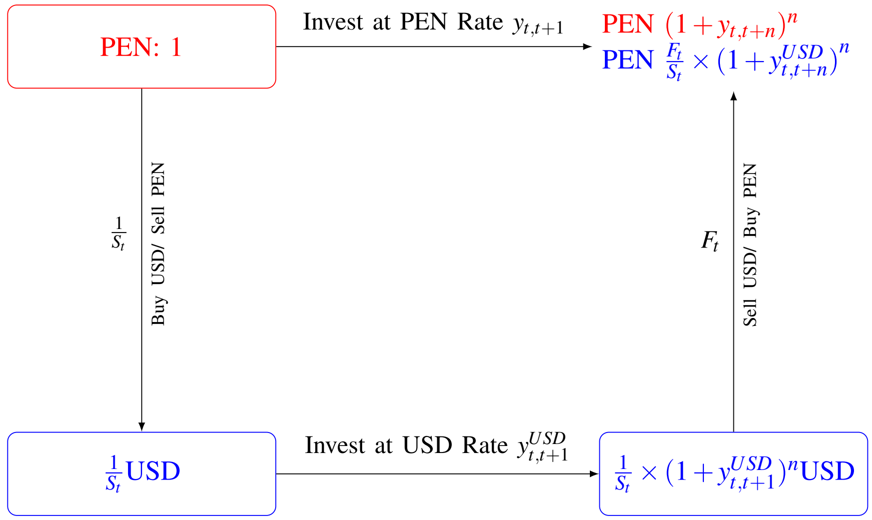

Figure 1: Example of Covered Interest Rate Parity (CIP)

CIP deviations imply that the rate of return of lending, say currency i, in the money market is different than the return of lending currency j but swapping the proceeds obtained from the loan in currency j to currency i once the loan matures. 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: $1+y_{t,t+1} = \frac{F_t}{S_t} \times (1+y^{USD}_{t,t+1})$.

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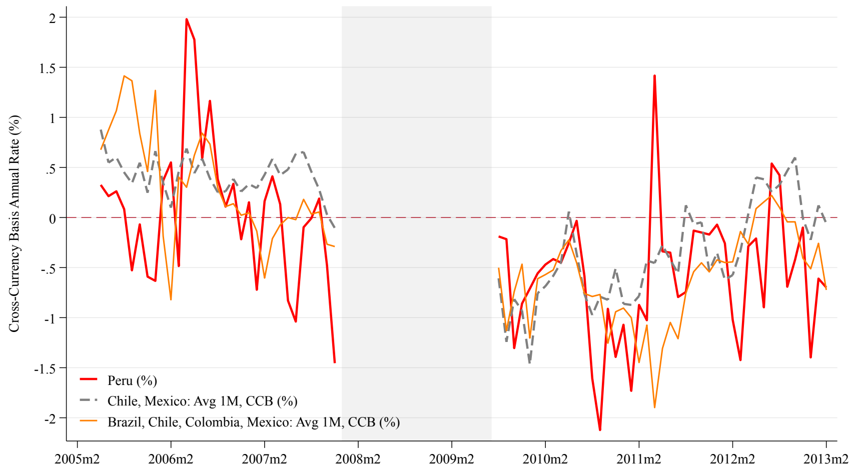
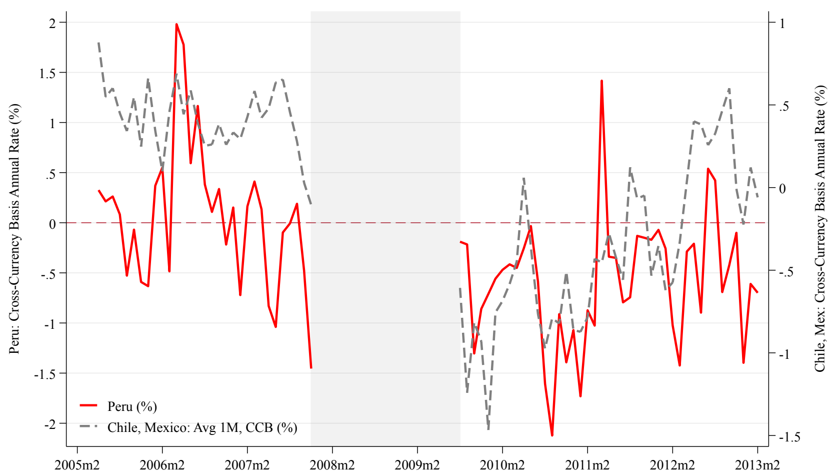


Panel A: Peru and other Latin American countries



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

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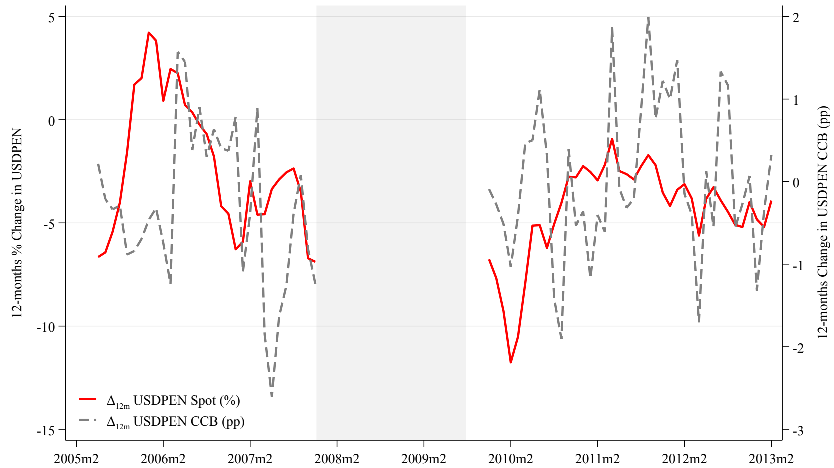
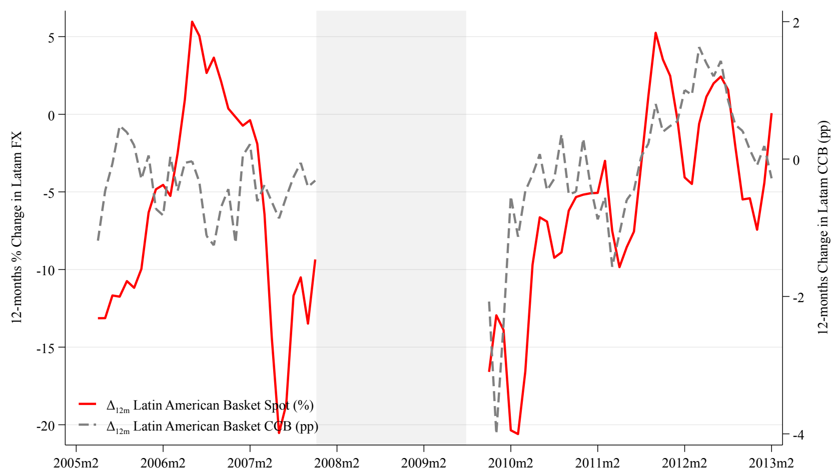


Panel A: USDPEN FX and Cross-Currency Basis in PEru



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

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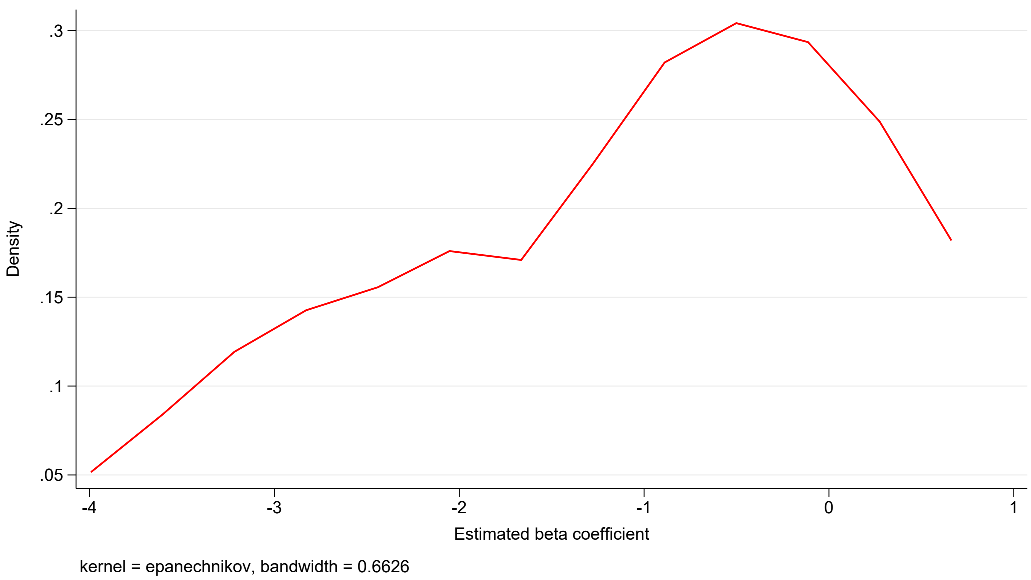
Figure 4: Smoothed density of the estimated $\hat{\beta}$ coefficients



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APPENDIX

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A.I. Tables

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Table A.I: 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
$\text{CCB}^{\text{Peru}}_{t-1} * (-\hat{\beta})$	-29.86**	21.74**	-0.736	2.319***	-39.68***	26.52***	-0.599	2.805***
	(-2.56)	(2.32)	(-0.28)	(2.73)	(-3.20)	(2.78)	(-0.26)	(3.19)
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	486530	486530	486530	448391	657357	657357	657357	610043
N Firm Cluster	10,847	10,847	10,847	10,333	12,346	12,346	12,346	11,818
N Date Cluster	77	77	77	74	77	77	77	77

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Table A.II: Effect of Arbitraging CIP deviations on Bank Lending: Baseline by Firm Size

This table shows the second stage results of the baseline model when segmenting the sample by firm size. The firm size corresponds to the SBS classification of "medium", "large" and "corporate" firms, which includes all firms with debt in the financial system above 90 million dollars. These are the firms for which I have loan-level data. For consistency across time, the SBS has also reconstructed the series to keep the firm size constant across time. The starting classification used is as follows. The largest firms, the "corporate" firms have yearly sales above 200 million soles (approximately 65 million dollars). The "large" firms have yearly sales between 20 and 200 million soles (6.5 to 60 million dollars), while the "medium" firms have had total debt with the financial system greater than 300,000 soles (nearly 100,000 dollars). For simplicity, the table below refers to the "corporate" firms as the "large" firms; the "large" as "medium" and the "medium" as the small. 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).

	Largest				Medium				Smallest			
	Log(PEN)	Log(USD)	Log(Total)	Ratio	Log(PEN)	Log(USD)	Log(Total)	Ratio	Log(PEN)	Log(USD)	Log(Total)	Ratio
$CCB^{Peru}_{t-1} * (-\hat{\beta})$	-29.96	30.00	3.047	1.745	-54.04***	24.89**	8.184*	2.590***	-24.60***	20.37***	0.787	1.821***
	(-1.36)	(1.63)	(0.35)	(1.52)	(-3.56)	(2.61)	(1.96)	(3.18)	(-2.76)	(2.90)	(0.39)	(2.82)
Firm * Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank * Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	55141	55141	55141	55141	258992	258992	258992	258992	1011250	1011250	996120	996120
N Firm Cluster	267	267	267	267	1,666	1,666	1,666	1,666	16,336	16,336	16,254	16,254
N Date Cluster	77	77	77	77	77	77	77	77	77	77	77	77

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Table A.III: Deposits and the role of the cross-currency basis and the FX

This table estimates linear regressions of banks' liabilities with the public (deposits) on the cross-currency basis and the FX. In all columns, the dependent variable is either PEN or USD Liabilities with the public and is stated at the header. The variables are written as percentage of assets (in the 0-100 scale). The independent variables are the USDPEN cross-currency basis (in %), the natural logarithm of the USDPEN spot exchange rate written in log points and their interactions with the bank-specific measure of arbitrage abilities, $\hat{\beta}$. Regressions were estimated using data at the bank-month level and with bank fixed effects. 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. HAC standard errors were used, allowing for 3-month autocorrelation. In addition, standard errors are clustered by month. t-stats are reported in parentheses and significance stars follow conventional levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	(1) PEN Dep	(2) USD Dep	(3) PEN Dep	(4) USD Dep	(5) PEN Dep	(6) USD Dep	(7) PEN Dep	(8) USD Dep
CCB (%)	-2.061***	2.582***	0.211	0.380	-2.708***	3.148***	-0.144	0.276
	(-3.70)	(4.62)	(0.97)	(1.45)	(-3.96)	(4.25)	(-0.54)	(1.23)
ln(FX)·100			-0.501***	0.486***			-0.553***	0.623***
			(-18.70)	(14.39)			(-19.30)	(21.59)
CCB·$\hat{\beta}$					0.602***	-0.527*	0.337*	0.0732
					(2.96)	(-1.78)	(1.79)	(0.33)
ln(FX)·100·$\hat{\beta}$							0.0485**	-0.126***
							(2.21)	(-6.00)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	873	873	873	873	873	873	873	873
Adjusted R2	0.0549	0.0925	0.479	0.481	0.0619	0.0975	0.490	0.520

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Table A.IV: Sensitivity of FX and Arbitrage Intensity

This table shows the summary statistics of the sensitivity of bank deposits to a 1% depreciation split by arbitrage intensity. The arbitrage intensity is measured by -β and estimated using Equation 5. The sensitivity of bank deposits to changes in FX has been estimated using Equation 7.

	Low -$\hat{\beta}$ $0 \leq -\hat{\beta} < 0.1$		Medium -$\hat{\beta}$ $0.1 \leq -\hat{\beta} < 2$		Large -$\hat{\beta}$ $2 < -\hat{\beta}$	
	Mean	Sd	Mean	Sd	Mean	Sd
$-\hat{\beta}$	0.03	0.03	1.11	0.29	2.70	0.57
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

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Table A.V: Sensitivity of FX and Arbitrage Intensity

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
$\text{CCB}_{t-1}^{\text{Peru}} * (-\hat{\beta})$	-24.14***	15.35***	3.041*	1.377***	-20.87**	21.18***	6.282***	1.495***
	(-2.81)	(2.74)	(1.78)	(2.74)	(-2.61)	(3.06)	(2.74)	(2.81)
$\log(\text{FX})_{t-1} * (-\hat{\beta})$	-2.462***	0.777**	-0.0153	0.125***	-2.777***	0.553	-0.221	0.134***
	(-4.68)	(2.18)	(-0.12)	(4.20)	(-5.65)	(1.34)	(-1.52)	(4.33)
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	1207464	1207464	1207464	1207464	1207464	1207464	1207464	1207464
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

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Table A.VI: Liquidity ratios (% of Total Assets) and the role of the cross-currency basis and the FX

This table estimates linear regressions of banks' liquidity ratios on the cross-currency basis and the FX. In all columns, the dependent variable is either PEN or USD liquidity ratio, defined as PEN or USD liquid assets divided by total assets, and is stated at the header. The variables are written in percentage (in the 0-100 scale). The independent variables are the USDPEN cross-currency basis (in %), the natural logarithm of the USDPEN spot exchange rate written in log points and their interactions with the bank-specific measure of arbitrage abilities, $\hat{\beta}$. Regressions were estimated using data at the bank-month level and with bank fixed effects. Columns 9-10 include additional Date FE. 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. HAC standard errors were used, allowing for 3-month autocorrelation. In addition, standard errors are clustered by month. t-stats are reported in parentheses and significance stars follow conventional levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	PEN LiqR	USD LiqR	PEN LiqR	USD LiqR	PEN LiqR	USD LiqR	PEN LiqR	USD LiqR	PEN LiqR	USD LiqR
CCB (%)	-2.053***	1.286***	-1.090***	1.058***	-0.820***	1.153***	-0.301	0.533*		
	(-5.40)	(4.22)	(-3.77)	(3.28)	(-3.20)	(3.24)	(-1.33)	(1.94)		
ln(FX)·100			-0.212***	0.0502			-0.107***	0.137***		
			(-8.29)	(1.40)			(-4.37)	(5.30)		
CCB·$\hat{\beta}$					-1.147***	0.124	-0.748***	0.471*	-0.748***	0.472**
					(-4.84)	(0.51)	(-3.20)	(1.95)	(-3.18)	(2.00)
ln(FX)·100·$\hat{\beta}$							-0.0979***	-0.0792***	-0.100***	-0.0744***
							(-5.21)	(-3.67)	(-5.21)	(-3.63)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	No	No	No	No	No	No	No	No	Yes	Yes
Observations	873	873	873	873	873	873	873	873	873	873
Adjusted R2	0.0979	0.0608	0.221	0.0716	0.145	0.0606	0.304	0.110	0.117	0.0331

A.II. 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:

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

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

A.III. 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

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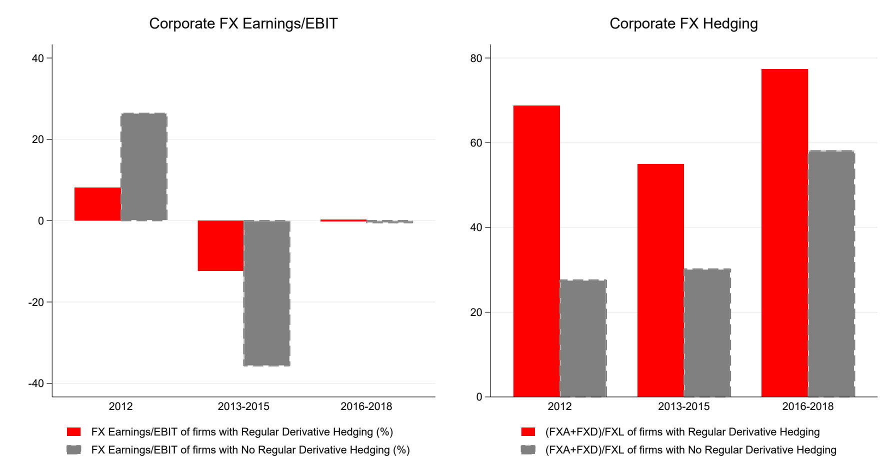
markets. In Peru, the sol depreciated 37% between 2013 and 2016. This significant depreciation can lead to changes in behavior and preferences of various economic agents. Moreover, it also led the Peruvian government to impose a series of regulations at the same time. Therefore, studying credit dynamics 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.[42]

Figure A.1: Firms FX losses and hedging



Source: Data from Figures 4 and 5 in 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

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

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loans to the private sector in foreign currency.[43] 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.

[43] 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)

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