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The Currency Composition of Firms' Balance Sheets and its Effect on Asset Value Correlations and Capital Requirements

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We extend the Tasche (2007) model on the asset correlation bias caused by a currency mismatch between assets and liabilities to the more realistic situation where some assets, and some, but not necessarily all, liabilities, are denominated in a foreign currency. To test the significance of the remaining bias we rely on a unique data base constructed by The Inter-American Development Bank (IADB) containing time-series of the asset- and liability currency composition of firms in a group of Latin American countries. Net currency mismatches are calculated and are found to vary from country to country. The correlation bias itself also varies significantly from country to country and has often been economically significant during the last 20 year-period. We find that the bias regularly is of the same magnitude as the correlation itself even in countries where the average firm has a fairly low degree of currency mismatch. Looking at market-wide corporate credit portfolios in four Latin American countries, we show that the credit risk, and associated Basel II capital charges, could increase by as much as a fifth, on average across our sample, if the actual currency mismatch in firms' balance sheets is acknowledged. In some cases the currency mismatch-induced capital charge could increase much more, sometimes to levels several times (hundreds of percent) the original capital requirement.

Keywords: asset correlation; bias; exchange rate; currency composition; currency mismatch
JEL classification codes: G10; F31; G21; G33; G15

1. Introduction

Portfolio-wide credit risk management relies on estimates of default dependencies and, for corporate credits, one of the most commonly used proxies for this dependency is the correlation among the asset values of the firms in the portfolio. The asset correlation is estimated as the correlation between the firms' (unobservable) asset returns, and the higher this correlation is the larger the (portfolio) credit risk. A complicating factor in estimations of asset correlations is that if firms have their assets and liabilities denominated in different currencies, i.e. there is a so-called currency mismatch, then the asset correlation will typically be biased. This bias was first mentioned in Tasche (2007) who also shows theoretically how the bias depends on (i) the volatility of the exchange rate changes, (ii) the volatilities of the asset value returns of the two firms and (iii) the correlation between the exchange rate changes and the two firms' asset returns. Byström (2013) builds on the theoretical results in Tasche (2007) and empirically estimates the mismatch-induced asset correlation bias in the US market. Byström (2013) finds the bias to be positive and large enough to result in a significant underestimation of portfolio credit risk. In a follow-up study, Byström (2014) focuses on the time-variation in the bias and on its theoretical and empirical dependency on the real-life currency dynamics. Byström (2014) finds the bias to fluctuate widely over time, and for shorter periods the bias even turns negative.

In this paper, we extend the theoretical analysis in Tasche (2007), which assumes a complete (100%) currency mismatch between assets and liabilities, to the more realistic situation where some assets (and some, but not necessarily all, liabilities) are denominated in a foreign currency, while the remaining are denominated in the domestic currency. The reason behind this step is that in the typical real-life firm the currency mismatch is often (much) lower than 100%. Therefore, we ask whether the bias calculated by Tasche (2007) perhaps is (much) less significant than previously assumed when the actual currency composition of the firms' balance sheets is taken into account. In other words, perhaps the actual degree of currency mismatch in the typical firm is lower than expected, and perhaps the Tasche (2007) and Byström (2013, 2014) results on the asset correlation bias is just a sideshow? To test this hypothesis, data on firms' balance sheet currency composition is required. However, high-quality data on the firm-specific details of corporate sector balance sheets is in short supply. In the empirical part of this paper we therefore rely on a data base developed by The Inter-American Development Bank (IADB) where annual accounting information for firms in several Latin American countries from 1992 to 2002 is collected and aggregated to the country level.

While, at first, our choice of investigating the real-life significance of the currency mismatch-induced asset correlation bias in a set of (rather peripheral) emerging market countries might seem less of a natural choice, there are, in fact, several compelling reasons for looking at this particular set of countries (other than the simple reason that we have not found any other detailed data base on currency compositions of firms' assets and liabilities).[1] First, the problems caused by currency mismatches in firms' balance sheets is likely to be worse in emerging countries than in advanced economies (Chan-Lau and Santos, 2006). Because of wide fluctuations in the value of the domestic currency, most firms in emerging countries find it easier to raise money if the debt is denominated in foreign currency (Kamil, 2004). This, coupled with emerging market firms' primarily domestic asset base, naturally leads to a more significant currency mismatch between assets and liabilities in these countries. Second, exchange rate risk is not easily hedged in the typical emerging economy since derivatives markets are often either non-existent or illiquid (Kamil, 2004), and this is likely to lead to stronger implications for the emerging market firm for a given currency mismatch. Third, emerging market currencies are often more volatile than major global currencies (Bleakley and Cowan, 2008) and since the asset correlation bias increases with the exchange rate volatility (Byström, 2014) the bias is likely to be larger among firms in emerging countries. Fourth, finally, the IADB data set includes uniform and consistent time-series data from several countries. This makes it possible for us to make a cross-country comparison of the effect of currency mismatches on the asset correlation bias for a group of countries (Chile, Colombia, Mexico and Peru) that differ in important dimensions such as the exchange rate regime, trade openness, banking sector dominance, market functioning and regulation etc.

As for our particular choice of Latin America, the main reason is, of course, data availability. In addition, however, one advantage of focusing on Latin American firms, other than the reasons listed above, is that due to the region's history of high degrees of dollarization the foreign exchange exposure of our group of Latin American firms is likely to be heavily skewed towards the US dollar (Cartas, 2010). Or as Tobal (2013) writes: "*distinguishing among foreign currencies does not seem to be a major issue [in Latin America] since the US dollar has traditionally been the currency denomination for foreign currency assets and liabilities in most economies in Latin America*". This tradition is an important advantage for us since any additional requirement of a detailed breakdown of firms' foreign-currency denominated assets and liabilities into different currencies would make it harder still, and potentially impossible, to find data suitable for our purposes.

The point of departure is that of a representative international investor holding large diversified but country-specific portfolios of corporate bonds or loans, perhaps segmented into different industries, in any of the four countries Chile, Colombia, Mexico and Peru. Such an investor is likely to need asset correlation estimates for credit risk management purposes and our aim is to investigate to what degree the asset correlation bias caused by the currency mismatch remains

[1] The data availability issue is particularly critical for our specific purpose since, in addition to the currency composition of assets

also after acknowledging that most firms have less than perfect (less than 100%) currency mismatch. The actual investors are not the only ones concerned about overseas credit risks, however. Domestic authorities such as central banks and supervisory agencies, concerned about systemic risk emanating from corporate balance sheets, should also be interested in asset correlations and asset correlation biases. This is perhaps particularly relevant in the Latin American region where national banks' domestic corporate exposure is quite significant (Kamil, 2004). Finally, it should be stressed that we do not have access to firm-level data but only country-level data (computed by IADB by aggregating firm-level data). Our quantitative results are therefore only strictly representative at the portfolio level.

In the empirical part of the study we show how the currency composition of balance sheets in Latin American companies has varied across the 1990s. The debt- and asset dollarization ratios are used to compute what we call *net currency mismatches* (CM_{net}) for each country. We find that the (average) net currency mismatch varies widely among the countries in the study. While it is more than 40% in Peru it is only 5% in Colombia, and we therefore also expect the asset correlation bias to be larger in some countries than in other. Regardless of country, however, we also find significant time-variation in the net currency mismatch.

Before turning to the estimation of the actual asset correlation bias, we then show, using a stylized theoretical analysis, how the asset correlation bias increases when the degree of mismatch increases. The theoretical analysis shows that the bias is found to be larger (in absolute terms) the smaller the asset correlation is. However, even though the size of the actual asset correlation bias is sensitive to the level of the asset correlation, the bias is of economic significance regardless of the size of the (one-currency) asset correlation.

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and liabilities, we also require leverage ratio data for the same set of firms.

We then turn to the computation of the correlation bias and, as expected, we find that the bias varies significantly among countries. For instance, while the asset correlation bias in Mexico often exceeds 0.20 the bias in Colombia rarely exceeds 0.01 across the twenty year long time-period. The bias varies significantly over time and, although it is mostly positive, it turns negative at times. A correlation bias of this size, i.e. 0.05, 0.15 or even 0.25, is clearly significant considering the asset correlation estimates figuring in the literature. In fact, we find that the bias, on average, is of the same magnitude as the correlation itself even among firms with a fairly low degree of currency mismatch.

As a final assessment of the economical relevance of the asset correlation bias we look at an average market-wide portfolio of corporate credits and at how the credit risk (the Basel II capital charge) of this portfolio is affected by the underestimation of asset correlations in the face of currency risk. On average, we find that our typical Latin America-focused investor (if it were a regulated bank) would have to set aside more than one additional fifth of capital (twenty percent) when acknowledging the asset correlation bias caused by the currency mismatch. That is, the actual credit risk on the investor's book is underestimated by more than twenty percent. What's more, we find that for some countries, and for certain time-periods, the credit risk/capital charge would increase much more than that, sometimes even to several times (hundreds of percent) the original values. Alas, the main implication of the paper is that even among firms where the currency mismatch is much lower than 100%, the exchange rate risk on the balance sheet can lead to a significant underestimation of asset correlations and, in turn, to an underestimation of portfolio credit risk and capital requirements.

Recent developments in the global financial markets underscore this risk further. Over the last couple of years, non-financial corporate borrowers in emerging-markets have issued increasing quantities of international debt securities, mostly in US dollars, to finance local assets. In doing so they have built up large currency mismatches with an increased risk for investors in these companies as the result (BIS, 2014). This behavior, coupled with recent international financial market developments, such as the sharp depreciations (versus the US dollar) of the Ukrainian hryvnia, the Russian ruble and several other emerging country currencies in the face of heightened geopolitical risks and falling oil prices, highlights the need for the currency mismatch induced asset correlation bias to be acknowledged by both market participants and regulatory agencies.

The rest of the paper is organized as follows. In chapter 2 we describe how we measure the effect of the exchange rate risk on the asset correlation estimate when the currency mismatch is not complete. Chapter 3 describes how we back out (the unobserved) asset values from stock prices using the Merton (1974) model, and chapter 4 presents the data. Chapter 5 presents and discusses the empirical results and, finally, chapter 6 concludes the paper.

2. The Currency Mismatch-Induced Asset Correlation Bias

As Tasche (2007) demonstrates, if firms' assets and liabilities are denominated in different currencies, then estimates of asset correlations are biased. The reason behind the bias is the additional layer of currency risk and Tasche (2007) quantifies the bias under the assumption that both asset value- and exchange rate movements follow geometric Brownian motions. If ρ denotes the ordinary (one-currency) asset correlation, i.e. the correlation between two firms' asset returns if all assets and liabilities are denominated in the same (local) currency, and if ρ^* denotes the two-currency asset correlation, i.e. the correlation between the asset returns if assets and liabilities are denominated in different currencies, Tasche (2007) shows that

$$\rho^* = \frac{\rho + \frac{r_1\tau}{\sigma_1} + \frac{r_2\tau}{\sigma_2} + \frac{\tau^2}{\sigma_1\sigma_2}}{\sqrt{\frac{\tau^2}{\sigma_1^{\ 2}} + 1 + \frac{2r_1\tau}{\sigma_1}}\sqrt{\frac{\tau^2}{\sigma_2^{\ 2}} + 1 + \frac{2r_2\tau}{\sigma_2}}} \tag{1}$$

where r_i is the correlation between the asset returns of firm i and the exchange rate changes, σ_i is the volatility of the asset returns of firm i and τ is the volatility of the exchange rate changes.

Now, if the currency mismatch is less than perfect, i.e. not all the firm's assets and liabilities are denominated in different currencies, then (1) has to be modified. For this purpose, we define a new variable that we call the net currency mismatch of a firm, CM_{net}. The net currency mismatch is computed as the difference between the debt dollarization ratio (dollar-linked debt as a percentage of total debt) and the asset dollarization ratio (dollar-linked assets as a percentage of total assets) of the firm

$$CM_{net} = \frac{Debt_{dollar}}{Debt_{total}} - \frac{Assets_{dollar}}{Assets_{total}}. \tag{2}$$

In other words, CM_{net} is a measure of how much more dollar-dependent the firm is on the liability side than on the asset side.

If all assets were denominated in local currency, i.e. $\frac{Assets_{dollar}}{Assets_{total}} = 0$, then CM_{net} would simply be equal to the debt dollarization ratio and the *effective* exchange rate risk of the debt of the firm would come from CM_{net} units of risky US dollar exposure and (1-CM_{net}) units of risk-free local currency exposure, and τ_{eff} would be the effective volatility of the (effective) exchange rate, i.e.

$$\tau_{eff} = CM_{net} \cdot \tau \tag{3}$$

If some of the assets were also denominated in foreign currency, CM_{net} would again be treated as the net exposure of the firm to the foreign exchange rate risk (some of the firm's debt exposure has now been mitigated by the firm's asset exposure) and τ_{eff} would again be the effective volatility of the exchange rate, i.e. the relevant measure of exchange rate risk. Only if the currency mismatch of the firm, unrealistically, happens to be 100% would $\tau_{eff} = \tau$. Now, the replacement of τ with τ_{eff} is the only necessary change to equation (1) since σ, the volatility of the asset return, is unchanged because, in the model, it is measured in local currency with the exchange rate overlay entirely covered by τ_{eff}, and r, the correlation between asset returns and exchange rate changes, is unchanged because the Pearson correlation coefficient is scale invariant (the correlation between asset returns and exchange rate changes is the same as the correlation between asset returns and the CM_{net} times larger effective exchange rate changes). In other words, the modified relationship between asset correlations when the currency mismatch is less than 100% is

$$\rho^*_{CM_{net}} = \frac{\rho + \frac{r_1(CM_{net}\cdot\tau)}{\sigma_1} + \frac{r_2(CM_{net}\cdot\tau)}{\sigma_2} + \frac{(CM_{net}\cdot\tau)^2}{\sigma_1\sigma_2}}{\sqrt{\frac{(CM_{net}\cdot\tau)^2}{\sigma_1^{\ 2}} + 1 + \frac{2r_1(CM_{net}\cdot\tau)}{\sigma_1}}\sqrt{\frac{(CM_{net}\cdot\tau)^2}{\sigma_2^{\ 2}} + 1 + \frac{2r_2(CM_{net}\cdot\tau)}{\sigma_2}}} \tag{4}$$

3. Estimating Asset Values

As demonstrated in equation (4), the asset correlation bias is a function of volatility- and correlation-estimates (σ_i and r_i) involving the asset value. Asset values are not observable, however, and unlike stock prices or exchange rates there is no market where the price of a firm's assets is determined. As a result, the asset value has to be estimated using models. The foremost model for this purpose is the Merton (1974) model and in this paper we rely on the Merton model to back out asset values from equity values and debt to equity ratios. Merton (1974) recognizes that a firm's equity is equivalent to a long position in a call option on the firm's assets with a strike price equal to the firm's debt level. This thinking is analogous to how ordinary call options are priced using the Black-Scholes model, and the equity value is therefore conveniently expressed using the mathematics of the Black-Scholes framework

$$V_E = V_A \cdot N(d_1) - e^{-r_f(T-t)} \cdot D \cdot N(d_2) \tag{5}$$

where

V_E = the market value of the firm's equity,

V_A = the market value of the firm's assets,

D = the firm's debt level,

T-t = the time to maturity of the firm's debt,

r_f = the risk-free interest rate,

$$d_1 = \frac{\ln\left(\frac{V_A}{D}\right) + \left(r_f + \frac{1}{2}\cdot\sigma_A{}^2\right)\cdot(T-t)}{\sigma_A\cdot\sqrt{T-t}},$$

$$d_2 = d_1 - \sigma_A\cdot\sqrt{T-t},$$

$N(\ )$= the cumulative normal distribution.

With the use of some Itō-calculus, a second equation that links σ_E and σ_A is derived

$$\sigma_E = \frac{V_A}{V_E}\cdot N(d_1)\cdot\sigma_A \tag{6}$$

and from (5) and (6) we can back out the asset value V_A. For a more detailed discussion on the estimation of asset values using the Merton model we refer to the literature (Merton, 1974; Crosbie and Bohn, 2003; Hull et al., 2005; Crouhy et al., 2000; Lee et al., 2011).

4. Data

The focus of this paper is on how the degree of currency mismatch on a firm's balance sheet affects the size of the asset correlation bias. In the empirical study, the balance sheet data comes from a cross-country data base put together by the Inter-American Development Bank (IADB). The data base contains data on the currency composition of assets and liabilities for publicly and non-publicly traded non-financial firms in Latin America on an annual basis across the time-period 1990 to 2002. The IADB data base is not only unique in its contents but it also has additional nice features, such as being uniform across countries as well as consistent across time (Kamil, 2004). Importantly, it provides balance sheet information for a significant share of the firm universe of each country and it includes firms with both publicly and non-publicly traded stocks, not just major listed firms.

From the IADB data base we collect end-of-year debt- and asset dollarization ratios for the average firm in the four countries Chile, Colombia, Mexico and Peru from 1994 to 2001.[2] The debt- and asset dollarization ratios are then used to compute the average country-wide net currency mismatch on an annual basis. In addition to the currency composition data we also collect average firm leverage data from the same IADB data base. Again, each year from 1994 to 2001 we collect end-of-year leverage ratios (total liabilities as a percentage of total assets) for the four countries Chile, Colombia, Mexico and Peru. From the yearly data, average daily firm debt levels are computed through a linear interpolation between successive end-of-year debt levels. The availability of average firm leverage data covering the exact same firms as the currency mismatch data is essential for us since it is needed for the estimation of the asset values and the correlation bias.

We only have access to data on the average firm in a country and we therefore compute the asset correlation bias, country by country, using hypothetical market-wide portfolios of domestic stocks. As a proxy for the equity valuation of these portfolios we use MSCI country stock indexes (in local currencies) for the four countries Chile, Colombia, Mexico and Peru from January 1994 to March 2014.[3] The data is available on a daily frequency and it is downloaded from Datastream. From this data, the equity (stock return) volatilities that are necessary for

[2] The number of firms used in the calculation of yearly country ratios is fairly large and ranges from a minimum of 99 (Colombia in the year 2000) to a maximum of 238 (Chile in the year 1998).

[3]The currency composition reported in the IADB data base is collected from publicly and non-publicly traded non-financial companies and is therefore possibly slightly different from that of the firms in the MSCI indexes. These indexes are the best proxies we can come up with, however, and we cannot, in any case, estimate asset values for firms without publicly traded stocks.

backing out the asset values using the Merton (1974) model are estimated as 250-day trailing historical standard deviations.[4]

As for exchange rates, we collect daily US dollar exchange rates from Datastream for the Chilean Peso (CLP), the Colombian Peso (COP), the Mexican Peso (MXN) and the Peruvian Nuevo Sol (PEN) from January 1995 to March 2014. The IADB data base does not present a breakdown of foreign-currency denominated assets/liabilities in terms of different currencies. We therefore assume that all foreign currency assets or liabilities in the firms in these countries are denominated in US dollars. We base our assumption on Gruic and Wooldridge (2013) who reports that the US dollar's share of new international placements by emerging market nationals has averaged 71% from 2010 to 2013. Furthermore, since Latin American countries are among the most dollarized countries in the world (Cartas, 2010) we have reason to expect that in Latin America, the US dollar's share is even larger than that number. As the risk-free interest rate, finally, we use the 3-month US Treasury Bill rate. The interest rate data is downloaded on a daily basis from Datastream.

5. Results

The aim of this paper is to relax the assumption in Tasche (2007) of a complete (100%) currency mismatch between a firm’s assets and liabilities, and instead look at the more realistic situation where some assets and liabilities are denominated in a foreign currency and some are denominated in the local currency.

We start the empirical part of the paper by showing how the currency composition of firms in the four Latin American countries Chile, Colombia, Mexico and Peru has varied across time. The firms’ debt- and asset dollarization ratios (dollar-linked debt and assets as a percentage of total

[4] Here, one could of course possibly use other more advanced estimates of volatility, such as ARCH or GARCH estimates.

debt and assets), as presented in Kamil (2004), are used to compute the net currency mismatch (CM_{net}) defined in chapter 2. The time-variation of the average country-wide CM_{net} is shown in Figure 1 and the degree of currency mismatch clearly differs among the four countries. While the average currency mismatch is more than 40% in Peru it is only 5% in Colombia (see Table 1). Figure 1 reveals some time-variation in the net currency mismatch but the variation is quite small. For instance, the various countries' CM_{net} curves do not cross each other even once; i.e. the relative ranking of country-wide currency mismatch remains unchanged throughout the 1994 to 2001 period. There does not seem to be any common trend in the four net currency mismatches and there is no common movement in the mismatch. To sum up, ceteris paribus, and assuming that the bias increases with the degree of mismatch, we can expect the asset correlation bias to be more significant in some of the countries, such as Peru and Mexico, than in, say, Colombia where the degree of currency mismatch is just a fraction of that in Peru (one eighth).

5.1. The Time Variation of the Asset Correlation Bias

Before turning to a comparison of the actual asset correlation biases for our four countries we will look at the theoretical relationship between the bias, $\rho *_{CE_{net}} - \rho$, derived from (4) and the currency mismatch, CM_{net}, using average values of r_i, σ_i and τ across all countries and years. We also assume that $r_1 = r_2$ and that $\sigma_1 = \sigma_2$, i.e. the assets of both firms are supposed to be identically volatile and have identical correlations with the exchange rate. Finally, in order to compute the bias we need an estimate of the original one-currency asset correlation ρ, i.e. the asset correlation among the portfolios of firms in the country if none of the firms has any currency mismatch on their balance sheet. The literature on portfolio credit risk contains a range of different asset correlation estimates and there does not seem to be a consensus on what a typical ρ should be. In the Basel II accord, for instance, where asset correlations are important components in the calculation of capital requirements for credit risk portfolios, it is recommended that the asset correlation lies somewhere in the 0.12 to 0.24 range for corporate borrowers (Lee et al., 2009). Empirical studies, however, often come up with correlation estimates that are both higher and lower than that. Zhang et al. (2008), for example, reports default implied asset correlation estimates from a range of previous studies. The estimates in that sample of studies range from close to zero to 0.15 with the bulk of studies reporting values in the 0.02-0.10 range. Zhang et al. (2008) themselves report somewhat higher asset correlations ranging from 0.08 to 0.30. Similarly, Hashimoto (2009) reports asset correlation estimates from a range of previous studies that use the Merton-type framework to model asset values. The estimates in that sample of studies ranges from roughly zero to 0.50 with most studies reporting values in the 0.05 to 0.10 range. Moreover, while we have not found any study looking specifically at the Latin American market, Düllmann et al. (2007) finds asset correlations for a large set of European non-financial firms to vary between 0.04 and 0.16. Considering the widely different asset correlation estimates in the literature, Düllmann et al. (2010) therefore uses two values, 0.10 and 0.25 respectively, in their own simulation study. We follow this path and compute the asset correlation bias for two extremes, $\rho = 0.05$ and $\rho = 0.40$, that we believe cover most asset correlation estimates reported in the literature.

Figure 2 reveals that the asset correlation bias derived from (4), indeed, increases with the degree of mismatch (which varies from 0% to 100%). The relationship is non-linear and the bias is more sensitive to changes in currency mismatch the lower the original asset correlation ρ is. In addition, a comparison of the bias with the correlation itself reveals that the size of the original correlation is material for the economic significance of the mismatch-induced asset correlation bias. While an original asset correlation of 0.40 at the most results in a bias of 0.17 even for a total 100% currency mismatch, an original asset correlation of 0.05 is biased more than 0.10 (i.e. tripled) already at a 50% currency mismatch. In fact, even at the low level of currency mismatch represented by Colombia in the 1990s, i.e. around 5%, the (theoretical) asset correlation bias is indeed measurable.

Having shed some light on the effect the degree of currency mismatch has, in theory, on the asset correlation bias we now turn to an empirical study, as in Byström (2014), of the size and time-variation of the actual bias for the countries and currencies above. While Byström (2014) looks at individual firms, however, we take a portfolio perspective. The reason for this is simply that we do not have access to firm-level data and we are therefore forced to take a country-wide view with asset correlations interpreted as correlations between diversified portfolios of corporate credits with identical time-series dynamics (represented by the country-wide MSCI stock index). Furthermore, the IADB data on the currency composition of firms' balance sheets in Latin America only stretches from end-of-year 1994 to end-of-year 2001. As a result, any calculation of asset correlation biases after 2001 will have to rely on historical values for the net currency mismatch. While the time-variation in the net currency mismatch, CM_{net}, indeed, is quite small across the time-period 1994 to 2002, as demonstrated by Figure 1, its dynamics across the period 2002 to 2014 is unknown to us. We therefore divide our empirical study into one proper "in-sample" study covering the time-period January 1995 to January 2002 and one "out-of-sample" study where the net currency mismatch is assumed to remain at its end-of-year 2001 level all through the time-period 2002 to 2014.

Figure 3 shows how the four US dollar exchange rates have varied over the time-period (normalized to start at the same level). All four Latin American currencies have weakened against the US dollar over the 20-year time-period and all currencies weakened significantly at the height of the financial crisis in 2008, but other than that demonstrate quite disparate behavior. The Peruvian Nuevo Sol is clearly the least volatile currency while the Mexican Peso is the most volatile (see Table 1).[5] While Figure 3 shows the currency behavior, Figure 4 shows how the asset values calculated using the Merton (1974) model have varied in the four countries over the 20-year time-period (normalized to start at the same level).[6] Again, the various countries demonstrate quite different behavior and the asset values of Chilean firms, for instance, are much less affected by the Lehman Brothers episode than those of Peruvian or Mexican firms. The Chilean asset values are also the least volatile among the four countries (see Table 1). Finally, when it comes to the co-variation among assets and exchange rates, Mexico stands out as the only country where the two are highly correlated (see Table 1).

Next, we turn to the actual computation of the bias, and the results are shown in Figure 5.[7] One initial observation to make from the bias-graphs in Figure 5 is that the bias varies very much from country to country. While the asset correlation bias in Mexico fluctuates in the 0.20-0.40 range for extended periods of time, the bias in Colombia, instead, rarely exceeds 0.01. Another observation is that the bias varies significantly over time. Sometimes, the bias is negative, but for all countries the bias is mostly positive. Another important observation to make is that the size of the (one-currency) asset correlation ρ matters for the size of the bias, both in relative terms and in absolute terms. The smaller the original asset correlation is the larger the *absolute* size of the bias is, regardless of the sign of the bias. Also, of course, if the original asset correlation is low, then a certain bias means more in *relative* terms; while the bias in Figure 5 is less alarming if the asset correlation estimate itself is large (0.40) it matters much more if the asset correlation estimate is

[5] Only the Mexican Peso is fully independently floating for the entire time-period (Kamil (2006)).

[6] The leverage ratios used in the Merton model calculation vary over time with a minimum value of 0.34 (Colombia in the year 2000) and a maximum value of 0.56 (Mexico in the year 2001).

[7] The time-varying parameters required for computing the bias; i.e. the correlation between the asset returns and the exchange rate changes, r_i, the volatility of the asset returns, σ_i, and the volatility of the exchange rate changes, τ, are all computed using a rolling window of 250 historical observations. And as explained above, we compute the bias for two extreme values of asset correlations, $\rho = 0.05$ and $\rho = 0.40$, that span the range of typical asset correlation estimates found in the literature.

low (0.05). In the latter case, the bias is actually comparable in size to the asset correlation itself for two of the four countries, and much larger in one country (Mexico). In fact, in the case of Mexico there are several periods when the asset correlation, including the bias, is more than four times larger than the traditional one-currency asset correlation. Obviously, such a significant bias has a major impact on the portfolio credit risk faced by anyone investing in Mexican credit. For Chile and Peru, the biased asset correlation ρ^* is lower, but still significant, at least when ρ = 0.05. One reason for the bias in Chile and Peru being smaller than that in Mexico is the lower currency volatility in the two former countries. This, in turn, is partly due to the exchange rates in Chile and Peru (and Colombia) not being fully independently floating for the entire time-period (Kamil (2006)). In Colombia, moreover, an additional reason for the much smaller asset correlation bias is the small Colombian net currency mismatch which, in turn, is at least partly due to the IADB data base excluding trade credit when calculating total dollar liabilities for Colombian firms (due to lack of data). This makes a significant difference since trade related dollar liabilities are common in Colombia (Kamil, 2004).

Table 2 presents the time-series averages of both the bias and the absolute value of the bias and it is clear that in the case of Mexico not only the extreme values of the asset correlation bias, but also the average values, are significant compared to the original asset correlation, at least when the latter is 0.05. To a lower degree the same is true for Chile and Peru. Finally, all averages are positive and there is no significant difference between the shorter "in-sample" period and the full "out-of-sample" period.

5.2. Estimation of Portfolio Credit Risk and Capital Requirements

To assess the economic significance of the asset correlation bias we compute the credit risk of the credit portfolios above with and without the asset correlation bias. In order to compute the credit risk we turn to Basel II and the capital requirement (capital charge) formula in the Internal

Ratings-Based (IRB) Basel II framework (BIS (2006)). Although this analysis was first intended for regulatory capital calculations, it has since earned general acceptance in the industry as a way of computing portfolio credit risk more generally.

The capital requirement for a credit portfolio exposure under the Basel II IRB framework is given by

$$Capital = LGD \cdot N\left(N^{-1}(PD) \cdot \sqrt{\frac{1}{1-\rho}} + N^{-1}(0.999) \cdot \sqrt{\frac{\rho}{1-\rho}} \right) - LGD \cdot PD \tag{7}$$

where $N(\ )$ is the cumulative normal distribution, $N^{-1}(\ )$ is the inverse of the cumulative normal distribution, *PD* is the default probability, *LGD* is the loss given default and ρ is the average pair-wise asset correlation (BIS; 2006, Zhang et al.; 2008, Lee et al., 2009). All through our analysis, ρ is interpreted as the average pair-wise asset correlation among the credit portfolios. We present the results both for the asset correlations used in the rest of the paper, i.e. 0.05 and 0.40, and for the maximum and minimum values in the range of asset correlations suggested by Basel II, i.e. 0.12 and 0.24.

The size of the capital charge depends on the default probability, *PD*, and the loss given default, *LGD*, of the typical firm(s) in the portfolio. As for the loss given default, we choose the 45% value required under the foundation approach in the Basel II framework, and for the default probability we choose four values ranging from the 0.03% minimum required probability in Basel II (for non-sovereign exposures) to a maximum value of 20% (p. 197 in BIS (2006)), i.e. 0.03%, 1%, 5% and 20% (BIS, 2006). Moreover, as we have seen above, the bias itself varies significantly across both time and countries and it also varies with the level of the original (one-currency) asset correlation. We have therefore chosen as the *representative bias* in the analysis below the bias averaged across all the values in the lower panel of Table 2 (i.e. across the entire time-period 1995 to 2014). This representative bias is 0.037.

The extent to which the credit risk, represented by the Basel II capital charge, is affected by the asset correlation bias is shown in Table 3. Regardless of the assumed default probability or (one-currency) asset correlation among the credits in the portfolio, the mismatch-induced asset correlation bias always increases the credit risk of the portfolio. The significance of the credit risk increase varies with both the default probability and the asset correlation, however, but only in the (fairly extreme) case when both the default probability and the asset correlation is very high at the same time does the bias have a negligible effect on the portfolio's credit risk. Overall, though, the percentage increase in credit risk when the bias is acknowledged is significant and it varies from a low of 2.8% (PD = 20% and ρ = 0.40) to a high of 70% (PD = 0.03% and ρ = 0.05).

We are looking at widely diversified portfolios of corporate credits in Latin America, and the default probability of the average firm in these portfolios most likely lies somewhere in the 1% - 5% range and the average correlation among two typical firms' asset returns in this portfolio is likely to lie in the 0.12 - 0.24 range. According to the numbers in Table 3, this therefore means that the credit risk, and the related Basel II capital charge, of the typical Latin America investor in our study is likely to be more than 20% underestimated when the currency mismatch is ignored. These are clearly economically significant numbers. It should be further stressed, however, that these are average values and in some cases, i.e. for some countries at certain times, the underestimation is significantly worse. In the case of Mexico during the recent financial crisis or during the Asian financial crisis, to take two extreme examples, the credit risk/capital requirement is either doubled, tripled or even quadrupled depending on how the default probabilities and the asset correlations are chosen (within the for our Latin American portfolios realistic 1% - 5% and 0.12 – 0.24 range, respectively). Likewise, of course, in other cases the underestimation is much less severe, and in the case of Colombia, to take another extreme example, the underestimation is never worse than one sixth of the original estimate.

To sum up, an investor's portfolio credit risk, and associated Basel II credit capital charge, can be significantly underestimated when the (partial) currency mismatch in the borrowing firms' balance sheets is ignored, at least in our study of Latin American exposures. On average, our typical Latin America investor would be required to set aside more than one additional fifth of capital (twenty percent) when acknowledging the asset correlation bias caused by the actual currency mismatch in our sample. And in some cases the capital charge could even increase to several times (hundreds of percent) the original one.

6. Conclusions

In this paper we extend the analysis in Tasche (2007) on the asset correlation bias caused by currency mismatch between assets and liabilities to a situation where only some assets (and some liabilities) are denominated in a foreign currency. This is a more realistic assumption than the one in Tasche (2007) and to test the significance of the bias in the face of a mere partial currency mismatch we rely on a unique data base reporting asset- and liability currency compositions of firms in the Latin American countries Chile, Colombia, Mexico and Peru. The data base is constructed by The Inter-American Development Bank (IADB) and contains country averages of firm-level currency mismatch data on an annual basis throughout the 1990s.

We define a measure called net currency mismatch (CM_{net}) and calculate such mismatches for each of the four countries. The average CM_{net} is found to vary significantly across our countries. The resulting asset correlation bias is also varying significantly across countries and over time, and for some countries it has, at times, been very large. Moreover, we find that the bias is of the same magnitude as the correlation itself even in countries where firms have balance sheets with a fairly low degree of currency mismatch, and despite the fact that three of the four countries have had extended periods when the currency volatility has been reduced due to government-managed exchange rate regimes. Finally, we show that portfolio credit risk, and associated capital requirements, on average across our Latin American countries, increases by as much as one fifth (twenty percent) if the actual currency mismatch in firms' balance sheets is acknowledged. Furthermore, for some countries, and for certain time-periods, we find that the credit risk/capital charge increases significantly more, sometimes even to several times (several hundreds of percent) the original one. As for the policy relevance of these results, they should be related to recent developments in the global currency markets where increased currency volatility as the result of heightened geopolitical risk and falling oil prices serves as a striking example of the importance of acknowledging currency mismatch in credit risk calculations, whether you are a risk-conscious investor or a government agency responsible for overall financial stability in the economy.

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Table 1 Descriptive Statistics. Average values across the "in-sample" time-period January 1995 to January 2002 and the "out-of-sample" time-period January 1995 to March 2014.

Descriptive Statistics				
	January 1995 to January 2002			
	Chile	**Colombia**	**Mexico**	**Peru**
$\boldsymbol{r}$	0.06	0.03	0.28	0.03
$\boldsymbol{\sigma}$ (%, annualized)	10.7	13.5	18.0	14.0
$\boldsymbol{\tau}$ (%, annualized)	6.3	6.6	15.0	4.2
Leverage (%)	37.0	35.0	50.8	47.6
$\boldsymbol{CM_{net}}$ (%)	17.7	5.7	33.2	41.1
	January 1995 to March 2014			
	Chile	**Colombia**	**Mexico**	**Peru**
$\boldsymbol{r}$	0.06	0.01	0.34	0.08
$\boldsymbol{\sigma}$ (%, annualized)	12.0	17.7	18.0	21.9
$\boldsymbol{\tau}$ (%, annualized)	8.8	9.0	12.3	4.4
Leverage (%)	-	-	-	-
$\boldsymbol{CM_{net}}$ (%)	-	-	-	-

Table 2 Asset Correlation Bias. Average values across the "in-sample" time-period January 1995 to January 2002 and the "out-of-sample" time-period December 1995 to March 2014. The time-varying parameters required for computing the bias; i.e. the correlation between the asset returns and the exchange rate changes, r_i, the volatility of the asset returns, σ_i, and the volatility of the exchange rate changes, τ, are all computed using a rolling window of 250 historical observations. The bias is computed for two values of asset correlations, ρ = 0.05 and ρ = 0.40.

Asset Correlation Bias					
		December 1995 to January 2002			
		Chile	**Colombia**	**Mexico**	**Peru**
$\rho = 0.05$	$\rho^*_{CE_{net}} - \rho$	0.021	0.0026	0.150	0.015
	$\lvert\rho^*_{CE_{net}} - \rho\rvert$	0.022	0.0034	0.150	0.028
$\rho = 0.40$	$\rho^*_{CE_{net}} - \rho$	0.014	0.0016	0.097	0.009
	$\lvert\rho^*_{CE_{net}} - \rho\rvert$	0.014	0.0022	0.097	0.018
		December 1995 to March 2014			
		Chile	**Colombia**	**Mexico**	**Peru**
$\rho = 0.05$	$\rho^*_{CE_{net}} - \rho$	0.024	0.0019	0.140	0.015
	$\lvert\rho^*_{CE_{net}} - \rho\rvert$	0.024	0.0033	0.140	0.020
$\rho = 0.40$	$\rho^*_{CE_{net}} - \rho$	0.015	0.0012	0.089	0.009
	$\lvert\rho^*_{CE_{net}} - \rho\rvert$	0.015	0.0021	0.089	0.018

Table 3 Capital Charges (Basel II IRB) for the average credit portfolio across the time-period December 1995 to March 2014. We compute the capital charge with and without the asset correlation bias for each of the four asset correlation values 0.05, 0.12, 0.24 and 0.40 and for each of the four default probabilities 0.03%, 1%, 5% and 20%. The loss given default (*LGD*) is always 45% and the representative asset correlation bias is at its time-series average value across the four countries, i.e. 0.037.

Capital Charge					
		December 1995 to March 2014			
		$PD = 0.03\%$	$PD = 1\%$	$PD = 5\%$	$PD = 20\%$
$\rho = 0.05$	Without bias	0.10%	1.65%	5.1%	10.7%
	With bias	0.17%	2.67%	7.7%	14.8%
$\rho = 0.12$	Without bias	0.25%	3.6%	9.9%	17.8%
	With bias	0.35%	4.7%	12.3%	20.8%
$\rho = 0.24$	Without bias	0.61%	7.5%	17.6%	26.1%
	With bias	0.75%	8.8%	19.9%	28.0%
$\rho = 0.40$	Without bias	1.26%	13.8%	27.2%	32.6%
	With bias	1.43%	15.4%	29.3%	33.5%

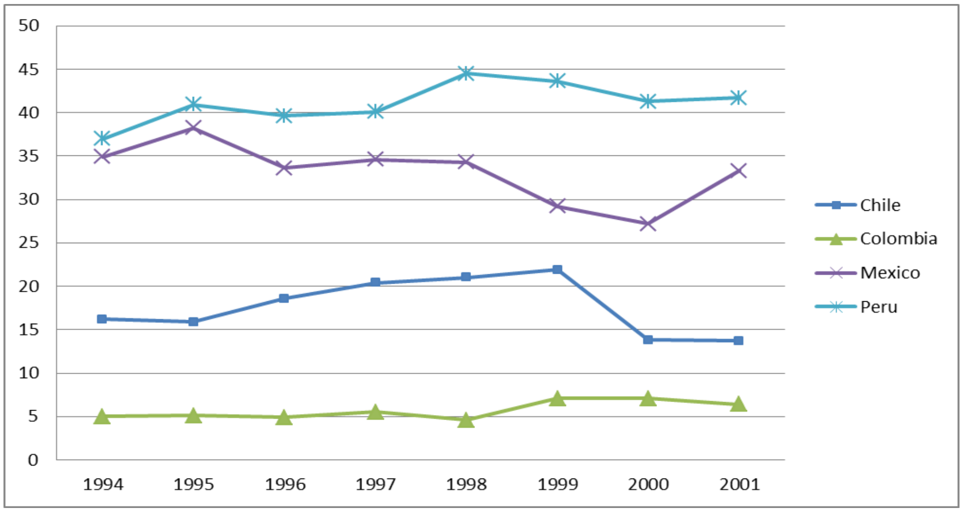

Figure 1 End-of-year percentage net currency mismatch, CM_{net}.

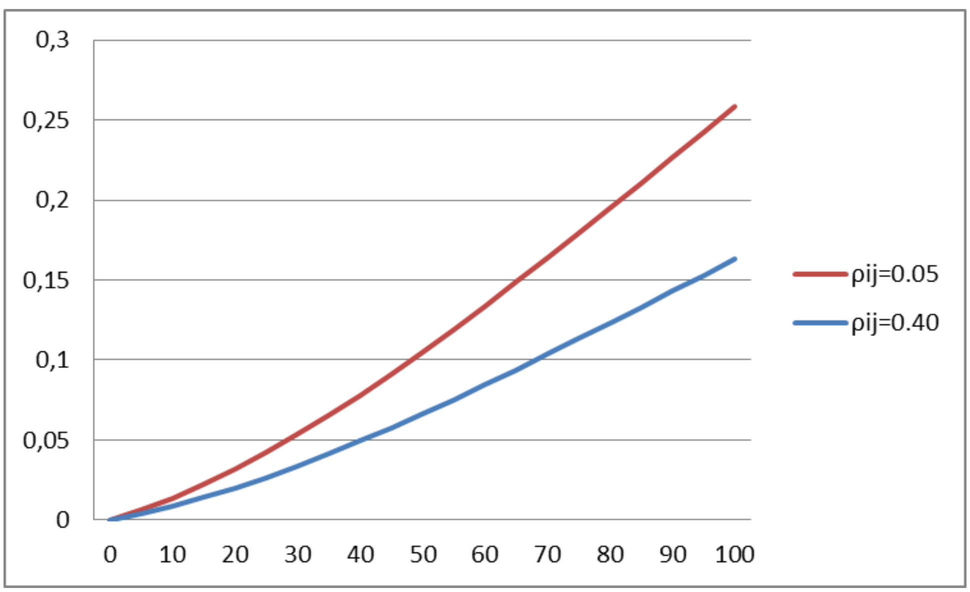

Figure 2 The asset correlation bias $\rho *_{CE_{net}} - \rho$ as a function of the percentage net currency mismatch, CM_{net}, using average values of r_i, σ_i and τ across all countries and years.

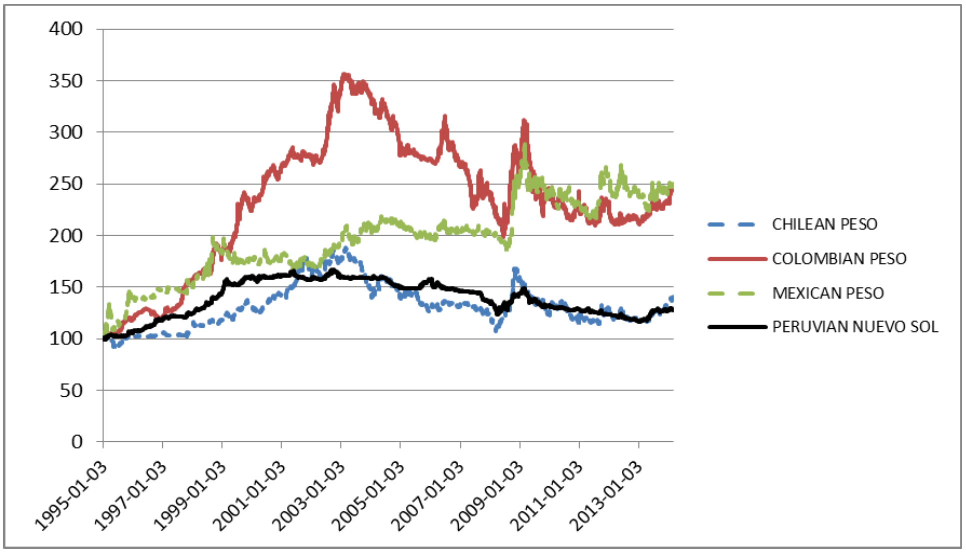

Figure 3 Daily US dollar exchange rates across the time-period January 1995 to March 2014 (normalized).

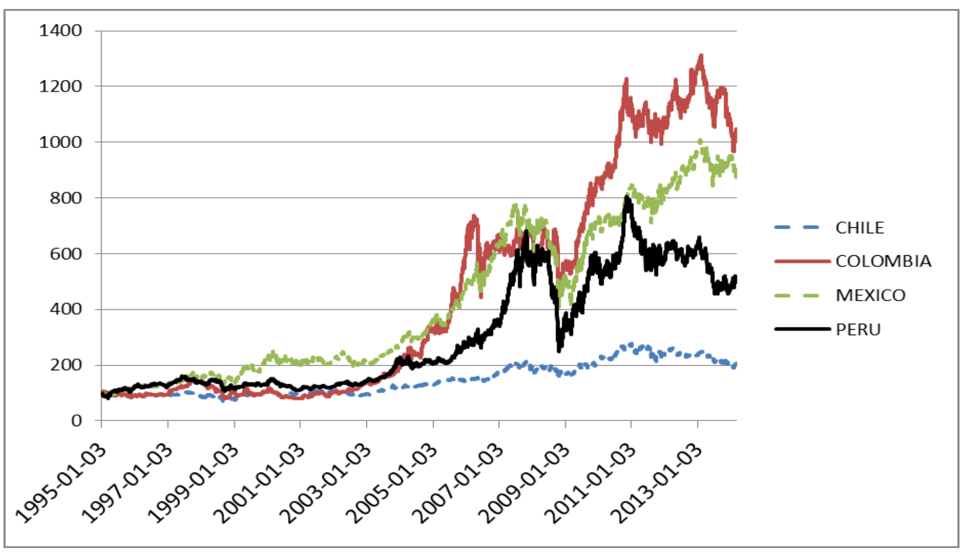

Figure 4 Daily asset values calculated using the Merton (1974) model across the time-period January 1995 to March 2014 (normalized).

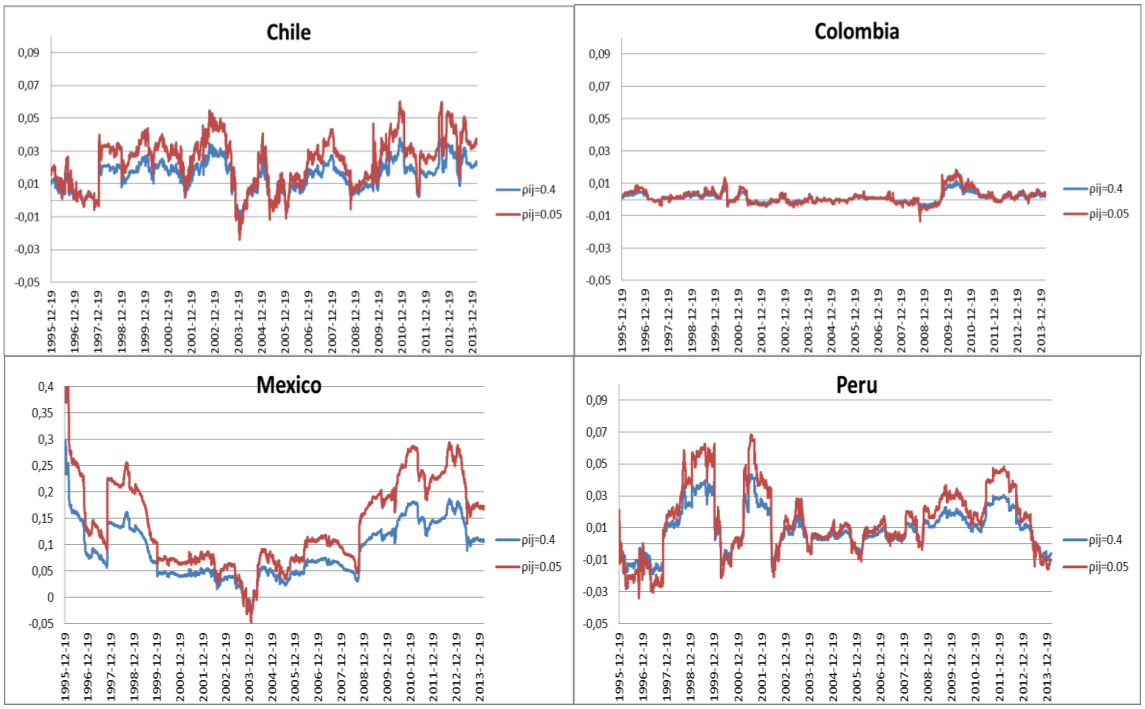

Figure 5 Daily asset correlation bias calculated across the time-period January 1995 to March 2014 (normalized). The time-varying parameters required for computing the bias; i.e. the correlation between the asset returns and the exchange rate changes, r_i, the volatility of the asset returns, σ_i, and the volatility of the exchange rate changes, τ, are all computed using a rolling window of 250 historical observations. The bias is computed for two values of asset correlations, ρ = 0.05 and ρ = 0.40.