Are Intermediary Constraints Priced?*

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Abstract

Violations of no-arbitrage conditions measure the shadow cost of intermediary constraints. Intermediary asset pricing and intertemporal hedging together imply that the risk of these constraints tightening is priced. We describe a "forward CIP trading strategy" that bets on CIP violations shrinking and show that its returns help identify the price of this risk. This strategy yields the highest returns for currency pairs associated with the carry trade. The strategy's risk contributes substantially to the volatility of the stochastic discount factor, is correlated with both other near-arbitrages and intermediary wealth measures, and appears to be priced consistently across various asset classes.

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Introduction

Covered interest rate parity (CIP) violations following the Global Financial Crisis (GFC) have been interpreted as a sign that intermediaries are constrained (e.g. Du et al. (2018b), Avdjiev et al. (2019), Fleckenstein and Longstaff (2018), Hébert (2018)). The intermediary asset pricing literature argues that constraints on intermediaries have important implications for asset prices (see, e.g., Kondor and Vayanos (2019), and He and Krishnamurthy (2017) for a survey). In this paper, we use CIP violations to measure the extent to which constraints bind, and provide direct evidence that the risk of constraints becoming tighter is priced. Our results offer novel evidence in support of intermediary-based asset pricing.

Following the GFC, new regulations (e.g. the Basel III leverage ratio rule and the U.S. supplementary leverage ratio) were introduced that require banks to maintain a minimum capital ratio against *all* assets, *regardless* of their risk characteristics. These leverage ratio constraints have been one of the most binding constraints facing large global banks post-GFC (Duffie (2017)). As a result, low-margin, balance-sheet-intensive, risk-free arbitrage conditions such as CIP can fail to hold. We use the term "balance sheet cost" to refer to the shadow cost associated with these constraints.[1]

The existence of liquid foreign exchange (FX) and interest rate derivatives across granular maturities allows us to directly measure innovations to the shadow cost of the relevant constraint from the term structure of CIP deviations. In particular, the difference between the ex-post realized short-term CIP deviation and the ex-ante forward-implied short-term CIP deviation is a measure of the "shock" to the shadow cost of the constraint.

[1]Because short-term CIP arbitrage trades have little mark-to-market risk, we interpret these deviations as primarily reflecting the shadow cost of non-risk-weighted capital constraints. However, nothing in our analysis proves that it is these constraints, and not other constraints, that bind with respect to cross-currency basis trades, and we do not rely on this interpretation in our empirical analysis.

We begin by considering a standard intermediary asset pricing model, augmented with a regulatory constraint. Because this model features arbitrage (CIP violations), there is not a single stochastic discount factor (SDF) that prices all assets. Nevertheless, every asset can be priced using an SDF (not the same for each asset) that is a function of the return on intermediary wealth and the magnitude of a cross-currency basis (i.e. a CIP violation). These SDFs differ only in terms of their mean, and that mean is a function of the assets' weight in the relevant regulatory constraint. Consequently, shocks to the cross-currency basis are innovations to the SDFs that price each asset. These shocks can be measured by a proposed "forward CIP trading strategy". We argue that the most straightforward test of this model is whether these forward CIP trading strategies, which bet on arbitrages becoming smaller, can earn excess returns.

We then proceed to the data, and estimate the excess returns of these forward CIP trading strategies. We define the forward CIP trading strategy as using FX forwards and forward-starting interest rate swaps to conduct a forward-starting CIP trade, and then unwinding the trade at its forward starting date. Consider a trader who, at time t, first enters into a forward-starting CIP trade to go long Japanese yen and short Australian dollars for three months between $t+1$ and $t+4$, with the currency risk fully hedged. We refer to this trade as a one-month forward three-month CIP trade. Then in a month, at $t+1$, the trader unwinds the forward CIP trade by going long Australian dollars and short Japanese yen for three months, cancelling all the promised cash flows of the forward CIP trade. The profits of this two-step forward CIP trading strategy are proportional to the difference between the market-implied one-month forward three-month CIP deviation observed at t and the actual three-month CIP deviation realized one month later at $t+1$. The forward CIP trading strategy has a positive (negative) return if the future CIP deviation is smaller (bigger) than the market-implied forward CIP deviation today.

The expected return on the forward CIP trading strategy offers a direct test of intermediary asset pricing theories in which large CIP deviations indicate that intermediaries are very constrained. Because the forward CIP trading strategy pays off poorly in these constrained states, if the constraints of financial intermediaries are indeed a priced factor, we should expect the forward CIP trading strategy to earn positive excess returns on average, as a risk premium to compensate investors for bearing the systematic risk exposure to variations in the shadow cost of intermediary constraints.

We find a significant risk premium for certain forward CIP trading strategies during the post-GFC period. Specifically, we study our forward CIP trading strategy for seven of the most liquid currencies: Australian dollar (AUD), Canadian dollar (CAD), Swiss franc (CHF), euro (EUR), British pound (GBP), Japanese yen (JPY), and U.S. dollar (USD). We consider both the cross-currency basis vis-à-vis the USD and the basis between two non-USD cross pairs.

Our model emphasizes the importance of the currency pairs with the largest spot cross-currency bases. We show that the average returns of the forward CIP trading strategies for these pairs are generally sizable and statistically significant post-GFC. In particular, the forward CIP trading strategy for the "classic carry" AUD-JPY pair has annualized average profit equal to 16 basis points and an annualized Sharpe ratio of roughly 1.2. In contrast, the mean return of the AUD-JPY forward CIP trading strategy pre-GFC is negligible.

We also examine the performance of the forward CIP trading strategies for portfolios of currency pairs. The returns of the forward CIP trading strategy (henceforth "forward CIP returns") are significant and positive post-GFC for portfolios of currency pairs with large interest rate differentials ("carry") or large spot cross-currency bases ("basis"). In contrast, we do not find evidence of risk premia when using a dollar strategy that equally weights all currencies vis-à-vis the USD. The strong performance of the carry and the basis portfolios and the lack of significance of the dollar portfolio are consistent with our model's prediction that the largest CIP violations are most informative about intermediary constraints. We also find that a portfolio based on the first principal component of the largest bases exhibits return characteristics that are similar to portfolios based on carry.

Intermediary constraints, if present, should affect many asset markets beyond the FX market. We show that CIP deviations are correlated with the first principal component of various other near-arbitrages. We also show that the returns of the forward CIP trading strategy are correlated with the proxies for intermediary wealth returns of He et al. (2017).

However, the correlation between the forward CIP return and the intermediary equity return measure of He et al. (2017) cannot explain the risk premium we uncover. We demonstrate this in regressions and more formally using the Bayesian factor model comparison method of Chib et al. (2020). These results justify the inclusion of the forward CIP return as an additional factor (along with the intermediary wealth return) in the SDF, consistent with our model. In particular, our results suggest that intermediaries are risk-tolerant and perceive strategies that perform poorly when investment opportunities are best to be especially risky.

We then test whether the excess returns of the tradable factors in this SDF (intermediary equity and the forward CIP return) are consistent with the prices of risk implied by the cross-section of assets, in an exercise building on He et al. (2017) and related to Hu et al. (2013) and Pasquariello (2014).[2] We cannot reject the hypothesis that this risk is priced consistently

[2]We focus on arbitrage opportunities post-GFC, which we attribute to constraints on financial intermediaries resulting from post-GFC regulations, whereas Hu et al. (2013) and Pasquariello (2014) study mostly pre-GFC price dislocations attributable to transaction costs, stale prices, and related issues. Their results can be seen as demonstrating that marginal utility is high when transaction costs are high.

across the various asset classes we consider, even when pooling across asset classes.

Our paper sits at the intersection of literature on arbitrage and on intermediary asset pricing. Recent empirical work on CIP violations (e.g. Du et al. (2018b)) has documented the existence and time series properties of spot CIP arbitrages, as well as the quarter-end dynamics of these arbitrages (the leverage ratio calculation only relies on quarter-end bank balance sheets in many non-U.S. jurisdictions).[3] Spot CIP arbitrage opportunities exist at very short horizons (e.g. overnight), making it difficult for any risk-based story to explain the existence of these arbitrages. This differentiates our work from the large literature on "limits to arbitrage" that focuses the convergence risk.[4] Instead, short-dated CIP deviations can exist because of *constraints* on intermediaries, and in particular, non-risk-weighted total leverage constraints in the post-GFC regulatory environment. Other authors, including Boyarchenko et al. (2018), also attribute the existence a broad class of arbitrages post-GFC to the leverage ratio constraints. Fleckenstein and Longstaff (2018) link the cash-derivative basis in the interest rate future market to the cost of renting financial intermediary balance sheet space. Hébert (2018) interprets these arbitrages through an optimal policy framework.

We broaden this burgeoning literature on constraints-induced arbitrage by studying the term structure of arbitrage violations, as opposed to spot arbitrage violations, and emphasizing the general asset pricing implications of these deviations. In particular, we show that

[3] Besides Du et al. (2018b), there has been a large recent literature on CIP deviations post-GFC. For example, Borio et al. (2016) argue that hedging demand of different national banking systems can help explain cross-sectional variations in CIP deviations. Rime et al. (2019) discuss the role of market segmentation in explaining CIP violations. Anderson et al. (2019) measure the amount of potential arbitrage capital available to global banks for CIP arbitrage. Liao (2019) finds that CIP deviations post-GFC affects the corporate sector's funding currency decision. Avdjiev et al. (2019) examine the relationship between CIP deviations, the dollar exchange rate, and the cross-border bank flows in dollars. Du et al. (2018a) and Jiang et al. (2018), and Krishnamurthy and Lustig (2019) use the CIP deviations for government bond yields to measure convenience yield differentials between safe-haven government bonds and study implications for exchange rate dynamics. Augustin et al. (2020) model the term structure of CIP deviations.

[4] See e.g. Shleifer and Vishny (1997), Liu and Longstaff (2003), Duarte et al. (2007) and Duffie (2010).

a significant fraction of the time-series variation in spot CIP violations is anticipated by the forward curve of CIP violations. This is true both generally and with respect to the quarter-end spikes documented in Du et al. (2018b).

Within the intermediary asset pricing framework (surveyed by He and Krishnamurthy (2017)), models such as Gabaix and Maggiori (2015) and Fang (2018) feature intermediary constraints as explanations of exchange rates dynamics. Much of this literature considers constraints that limit intermediaries' ability to access investments with favorable risk/return trade-offs, whereas we emphasize constraints (such as non-risk-weighted leverage constraints) that inhibit true arbitrages. In this respect, our model builds on Garleanu and Pedersen (2011). We also contribute to this literature by emphasizing the importance of intertemporal hedging considerations, following Campbell (1993) and Kondor and Vayanos (2019), whereas much of the literature (e.g. He and Krishnamurthy (2011), Garleanu and Pedersen (2011), and He et al. (2017)) relies on log utility for intermediaries and neglects these considerations.

In taking the model to the data, we are building on He et al. (2017), Adrian et al. (2014), Hu et al. (2013), and Haddad and Muir (2020). Our model can be thought of as nesting the SDFs discussed by Adrian et al. (2014) and He et al. (2017). When risk aversion is equal to one, the intertemporal terms in our SDF vanish, and the intermediary wealth return is the SDF (as in He et al. (2017)). When risk aversion is equal to zero (the risk-neutral case), the SDF consists only of intertemporal hedging terms, which are proxied for by the shadow cost of intermediary constraints (as in Adrian et al. (2014)). We measure these shadow costs using CIP violations, which we argue in the context of our model is a clean and valid measure. In contrast, Adrian et al. (2014) measure these shadow costs using leverage. It is not clear, however, whether the price of leverage risk comes from its correlation with intermediary wealth returns, its correlation with intermediary shadow costs, or some combination thereof.

Closer in spirit to our exercise is Hu et al. (2013), who measure intermediary constraints using Treasury yield curve dislocations. A comparison to this approach reveals the second key advantage of using CIP violations to measure shadow costs: we can directly estimate the price of risk from our forward arbitrage trading strategy, instead of relying on the usual cross-sectional asset pricing analysis. We focus our analysis on this direct estimate of the price of risk, and verify in our cross-sectional analysis that the price of risk we infer from the cross-section is consistent with the price of risk we estimate directly.

1 Hypothesis and Model

In the empirical analysis that follows, we will test the hypothesis that changes in the magnitude of cross-currency bases (i.e. CIP violations) are priced. This hypothesis is motivated by a specific intermediary asset pricing model, which we outline below and detail in the Internet Appendix Section B. Our paper is primarily an empirical study; the purpose of the model is to motivate our hypothesis and to provide a framework to interpret our results. However, we should acknowledge at the outset that there are other possible interpretations of our empirical results, some of which we discuss after presenting those results.

Our model is designed to capture three key ideas:

1. Arbitrage violations measure investment opportunities. This is true in our model because arbitrage violations can exist only if constraints on intermediaries bind, and constraints on intermediaries bind only if they prevent those intermediaries from taking advantage of investment opportunities (this is the definition of "bind").

2. Investment opportunities are likely to be best when intermediary wealth is low. For this reason alone, if our empirical proxies for intermediary wealth are imperfect, we should

expect changes in arbitrage violations to be a priced risk controlling for imperfect wealth proxies.

3. Even holding wealth fixed, changes in investment opportunities can be a priced factor. In the presence of good investment opportunities, the marginal value of wealth might be high, because it allows intermediaries to take advantage of those opportunities, or it might be low, because good investment opportunities enable larger payouts. The sign of this effect is determined by the intermediary's intertemporal hedging concern.

The model is a discrete time version of He and Krishnamurthy (2011) that incorporates a regulatory constraint (building on He and Krishnamurthy (2017)) and intertemporal hedging considerations (following Campbell (1993)). Under this regulatory constraint, each asset that the intermediary can hold (indexed by $i \in I$) is subject to an asset-specific weight k^i. As a result, each asset the intermediary owns is priced by a log SDF m_{t+1} of the form

$$m_{t+1} = \mu_t(k^i) - \gamma r^w_{t+1} + \xi |x_{t+1,1}|, \tag{1}$$

where r^w_{t+1} is the return on the manager of an intermediary's wealth portfolio and $|x_{t+1,1}|$ is the absolute value of a one-period cross-currency basis. The dependence of the mean of the SDF on k^i reflects the effect of the regulatory constraint, and $|x_{t+1,1}|$ serves as a proxy for future investment opportunities. Note that assets with different risk weights k^i will be priced by different SDFs, leading to arbitrage opportunities; however, all of these SDFs agree on the risk prices γ and ξ.

The SDFs in (1) nest the SDFs discussed in Adrian et al. (2014) and He et al. (2017). When $\gamma = 1$, $\xi = 0$, and the SDF is exactly the intermediary wealth return as in He et al. (2017). When $\gamma = 0$, $\xi > 0$, meaning that the marginal value of wealth is high when future investment opportunities are best (as in Adrian et al. (2014)).[5]

Our hypothesis is that ξ is economically and statistically distinguishable from zero. The key idea behind this hypothesis is that the cross-currency basis $|x_{t,1}|$ is both a literal arbitrage and a measure of the investment opportunities available to intermediaries at time t. An arbitrage can exist only if intermediaries are constrained and cannot take advantage of an otherwise attractive investment opportunity. In the presence of such constraints, an intermediary concerned with hedging against changes in future investment opportunities should perceive assets whose returns are correlated with $|x_{t+1,1}|$ as particularly risky or safe, depending on the sign of the intermediary's intertemporal hedging concerns.

Campbell (1993) shows that SDFs with the form of (1), interpreting $|x_{t+1,1}|$ as an arbitrary random variable as opposed to a cross-currency basis and without a mean that depends on k^i, can be derived using CRRA or Epstein-Zin preferences (and assuming log-normality and homoskedasticity). In this case, $|x_{t+1,1}|$ must proxy for the revision in expectations about future investment opportunities. That is,

$$|x_{t+1,1}| - E_t[|x_{t+1,1}|] \propto \sum_{j=1}^{\infty} \rho^j (E_{t+1} - E_t)[r^w_{t+1+j}].$$

The sign of the coefficient ξ depends on whether the relative risk aversion[6] coefficient γ is greater or smaller than one ($\gamma < 1 \Leftrightarrow \xi > 0$). Intertemporal hedging concerns on their own can be used to justify any SDF, including the ones we consider. Our point is that there are specific reasons to expect arbitrage violations to predict future investment opportunities.

[5] Adrian et al. (2014) build on Brunnermeier and Pedersen (2009) (effectively a three-period model), and therefore summarize investment opportunities with single future return. Adrian et al. (2014) also assume investment opportunities are negatively correlated with intermediary leverage; it is not a priori clear this should be the case, but it holds in the Brunnermeier and Pedersen (2009) model.

[6] As discussed in Campbell (1993), this result holds for both CRRA and Epstein-Zin preferences. That is, it is γ and not the elasticity of intertemporal substitution coefficient that determines the sign of ξ.

Suppose the manager of an intermediary has CRRA or Epstein-Zin preferences and holds an equity claim on the intermediary.[7] The intermediary is subject to a regulatory constraint,

$$\sum_{i \in I} k^i |\alpha_t^i| \leq 1. \tag{2}$$

Here, α_t^i is the intermediary's holding of asset i at time t as a share of the intermediary's equity, and k^i is the asset-specific weight mentioned above. This constraint captures some of the key features of leverage ratios and risk-weighted capital requirements. First, to the extent that the k^i differ across assets, the constraint can capture risk-weights. Second, the constraint is relaxed by increasing the level of equity financing relative to debt financing, holding fixed the dollar holdings of each asset. Third, the constraint can omit entirely certain assets such as derivatives, consistent with how some leverage constraints and risk-weighted capital constraints operate. To simplify our exposition, we will assume in what follows that derivatives are not included in the regulatory constraint.[8]

The manager's first-order condition for the portfolio share α_t^i is

$$E_t[\exp(m_{t+1})(R_{t+1}^i - R_t^b)] = \lambda_t^{RC} k^i sgn(\alpha_t^i), \tag{3}$$

where m_{t+1} is the manager's log SDF, R_{t+1}^i is the gross return on asset i, $R_t^b = \exp(r_t^b)$ is the gross rate on the intermediary's debt between dates t and $t+1$, $sgn(\cdot)$ is the sign function,

[7]We follow He and Krishnamurthy (2011) in assuming that the manager must hold an equity claim of a certain size to avoid moral hazard. For the remainder of this section, we will assume that this constraint does not bind. We make this assumption both for simplicity and to emphasize that the regulatory constraint can bind even if the equity constraint does not. For formulas that extend to the case with a binding constraint, and a more detailed discussion of this issue, see Internet Appendix Section B.

[8]This particular functional form follows He et al. (2017). Its details are not essential for our result; in particular, we could easily accommodate a constraint that treats long ($\alpha_t^i > 0$) and short ($\alpha_t^i < 0$) positions asymmetrically. Considering regulatory constraints that include derivatives complicates the analysis but does not alter the main predictions of the model that we will take to the data.

and λ_t^{RC} is the (scaled) multiplier on the regulatory constraint.[9] Let us apply this equation to two portfolios of assets: the cross-currency basis arbitrage and the wealth portfolio.

Let S_t denote the exchange rate at time t (in units of foreign currency per U.S. dollar), and let $F_{t,1}$ denote the one-period ahead forward exchange rate. We define the spot one-period cross-currency basis as

$$X_{t,1} = \frac{R_t^b}{R_t^c}\frac{F_{t,1}}{S_t} - 1$$

where R_t^c is the foreign currency risk-free rate, and let $x_{t,1} = \ln(1 + X_{t,1})$ be the log version. The first order condition is, taking absolute values,

$$E_t[\exp(m_{t+1} + r_t^b)]|1 - \exp(-x_{t,1})| = \lambda_t^{RC} k^c, \tag{4}$$

where k^c is the risk-weights of the foreign currency risk-free bond.

The key takeaway from this equation is that the absolute value of the cross-currency basis can be used to measure the shadow cost of the regulatory constraint. Intuitively, if an arbitrage opportunity is available to the intermediary, the intermediary would take advantage of it if the intermediary could; therefore, the intermediary must be constrained. The size of the arbitrage opportunity can be used to measure the degree to which the constraint binds (a point emphasized by Hébert (2018)).

Let us now consider the first-order condition applied to the entire wealth portfolio (i.e. taking the α_t^i-weighted sum of Equation (3) across the various assets). In this case, by the definition of the constraint,

$$E_t[\exp(m_{t+1})(\exp(r_{t+1}^w) - \exp(r_t^b))] = \lambda_t^{RC}. \tag{5}$$

[9]In the particular case in which $\alpha_t^i = 0$, we have the usual inaction inequalities, $-\lambda_t^{RC} k^i \leq E_t[\exp(m_{t+1})(R_{t+1}^i - R_t^b)] \leq \lambda_t^{RC} k^i$ (see Internet Appendix section B).

This equation captures the intuition that the shadow cost of the constraint is equal to the marginal value of the forgone investment opportunities. The constraint binds only if the intermediary has valuable investment opportunities it cannot exploit due to the constraint.

Combining these two equations to eliminate the shadow cost,

$$\frac{E_t[\exp(m_{t+1})(\exp(r^w_{t+1} - r^b_t) - 1)]}{E_t[\exp(m_{t+1})]} = \frac{|1 - \exp(-x_{t,1})|}{k_c}.$$

That is, the arbitrage available at time t can measure the investment opportunities available at time t. Log-linearizing and assuming homoskedasticity (see (A1) in Internet Appendix Section B for details),

$$(E_{t+1} - E_t)[r^w_{t+1+j}] = (E_{t+1} - E_t)[r^b_{t+j} + k_c^{-1}|x_{t+j,1}|].$$

Thus, revisions in expected future cross-currency bases measure revisions in future investment opportunities more generally. Moreover, these effects are amplified by leverage k_c^{-1}. Because innovations to the cross-currency basis are persistent, we can proxy for revisions in expectations about $|x_{t+j,1}|$ with the innovation to $|x_{t+1,1}|$. This result, combined with intertemporal hedging, justifies the SDFs of Equation (1).

This argument (described in more detail in the Internet Appendix) motivates our empirical exercise, which attempts to measure price of cross-currency basis risk (ξ). The most direct way to estimate this price of risk is to study a derivative contract whose payoff is linear in $|x_{t+1,1}|$. If such a contract has an excess return that cannot be explained by the covariance between $|x_{t+1,1}|$ and the other parts of the hypothesized SDF (i.e. r^w_{t+1}), we should conclude that innovations in the cross-currency basis are indeed a priced risk factor (or at least correlated with an omitted factor). The forward CIP trading strategy that we construct in our empirical analysis is exactly this derivative contract. The following remarks discuss some basic insights from the model that guide our empirical analysis.

Correlation between Factors. The two factors in our SDFs (the intermediary wealth return and the basis) likely move together. Because our model treats asset prices as exogenous, it makes no predictions about this co-movement. Most general equilibrium intermediary asset pricing models (e.g. He and Krishnamurthy (2011)) predict that investment opportunities are best for intermediaries precisely when intermediaries have lost wealth, and hence we should expect a negative correlation between the two factors.

Omitted Factors. Equation (1) likely omits important elements of the SDF. Any factor that predicts revisions in expectations about future investment opportunities (about the future cross-currency basis, future risk-free rates, or, in a heteroskedastic model like Campbell et al. (2018), future volatility) should also enter the SDFs.

Noisy Intermediary Wealth Return Measures. Our proxies for intermediary wealth returns are measured with noise. For this reason, we will never be able to definitively prove that the excess returns we document are caused by intertemporal hedging concerns as opposed to by correlation with intermediary wealth returns that is not captured by our proxies. Moreover, in light of the point on omitted factors above, any atheoretical factor that has explanatory power above and beyond our two SDF factors can be rationalized either as providing a better measure of intermediary wealth returns or as a proxy for future investment opportunities. We refrain from running "horse race" regressions with additional factors because of this lack of a clear interpretation.

Sources of Variation. Our model shows that the shadow cost of regulatory constraints can be measured with CIP violations, but is silent on why CIP violations vary over time. We expect that supply shocks (low intermediary net worth), demand shocks (e.g. changing customer preferences), and changes in the structure of the regulatory constraint will all affect the shadow cost of the constraints on intermediaries. Our results demonstrate that, regardless of what is driving changes in these shadow costs, the SDFs of Equation (1) should price the assets available to the intermediary.

CIP vs. Other Arbitrages. Our model places no special emphasis on CIP violations. Any arbitrage that intermediaries engage in could be used to measure λ_t^{RC}. In subsection 4.1, we argue that among various arbitrages and near-arbitrages documented in the literature, CIP violations are unique in terms of our ability to accurately measure the spot arbitrage x_t and to construct a trading strategy that directly bets on x_t becoming larger or smaller in the future. We also document that spot CIP violations are highly correlated with other arbitrages, consistent with our model.

Magnitudes. Shocks to the cross-currency basis are small (basis points). However, intermediaries are quite levered, meaning that k^c might be small, consumption-wealth ratios for managers are likely small (meaning ρ is close to one), and innovations to the basis are persistent. These forces increase the price of cross-currency basis risk, and might cause a significant fraction of the volatility of the SDFs to be attributable to innovations in the basis.

Leverage Constraints post-GFC. In our model, CIP violations can arise only if the regulatory constraint binds for this riskless arbitrage. In the absence of a binding constraint, CIP violations cannot exist in equilibrium, even if the inside equity constraint binds. The lack of CIP violations pre-GFC in the data is therefore consistent with the absence of non-risk-weighted leverage constraints for many banks prior to the GFC. The persistence of CIP violations and other short-term arbitrages (such as the interest rate on reserve arbitrage) post-GFC is consistent with binding leverage constraints under Basel III.[10]

Heterogeneity Across Currencies. Our description of the model has emphasized a single cross-currency basis, whereas our empirical analysis will consider a variety of currency pairs. In the context of the model, all of the cross-currency bases that the manager invests in will have the maximal arbitrage per unit risk weight available. Any basis that offers an inferior level of arbitrage per unit risk weight will receive a zero portfolio weight. In particular, if the risk-weights are identical across currencies, the manager would invest only in the basis with the largest arbitrage violation. In reality, there are several reasons why a smaller measured basis might nevertheless be actively traded by intermediaries.

- Intermediaries may have some degree of market power, and face different demand curves across currencies (Wallen (2020)). Intermediaries are also heterogeneous, and in particular have different deposit bases and access to wholesale funding markets across currencies.[11]

- Some regulatory metrics, such as the liquidity coverage ratio (LCR), are monitored on the currency-by-currency basis.[12] In addition, the allocation of CIP arbitrage activities across currency pairs also affects the distribution of liquidity across different

[10]Non-U.S. banks did not face a non-risk-weighted leverage ratio requirement prior to the 3% leverage ratio requirement under Basel III. U.S. banks had a 3% leverage ratio requirement prior to Basel III, and a 5-6% leverage ratio requirement under Basel III. During the pre-GFC period, other kinds of constraints might have been binding, and CIP violations are not the right way to measure the shadow cost of such constraints.

[11]See, for example, Rime et al. (2019) on the impact of money market segmentation on CIP deviations.

[12]Even though the Basel III LCR requirement is calculated at the aggregate level across all currencies, currency-specific LCRs are nevertheless actively monitored by bank examiners and bank internal managers.

entities and jurisdictions, which could make liquidity stress tests and resolution planning rules more binding (Correa et al. (2020)). These considerations would lead to the intermediary having different shadow costs for different currencies.

- The meaning of the benchmark OIS rate varies across currencies, and it may be a better proxy for the banks' borrowing/lending costs in some currencies than in others. Heterogeneity in the basis might be caused in part by a lack of perfect comparability of interest rates across currencies. We discuss this point in more detail in Section 3.

In our empirical analysis, we strike a balance between the literal interpretation of our model and these real-world considerations by focusing on the currency pairs with the largest and most robust bases.

2 Forward CIP Arbitrage

We describe the forward CIP trading strategy that bets on the size of the future cross-currency basis in three steps. First, we revisit "spot" cross-currency bases (as in Du et al. (2018b)), and describe the cross-currency bases based on overnight index swap (OIS) rates that we use in our empirical analysis.[13] Second, we discuss "forward" cross-currency bases, constructed from forward-starting OIS swaps and FX forwards. Third, we introduce our forward CIP trading strategy, which initiates a forward-starting cross-currency basis trade but then unwinds the trade once it becomes a spot trade. This trading strategy is not itself an arbitrage, but rather a risky bet on whether available arbitrages will become bigger or smaller.

[13]For robustness, in Internet Appendix Tables A5 and A6, we also consider a forward CIP trading strategy based on interbank offer rates (IBOR) and forward rate agreements (FRAs) indexed to these IBOR rates. The OIS and FRA data for the pre-GFC period appear less reliable (more missing or erroneous values) than the data for the GFC and post-GFC periods.

We study cross-currency bases in seven major currencies, AUD, CAD, CHF, EUR, GBP, JPY and USD.[14] We examine the bases of both individual currency pairs and portfolios of currency pairs, although our portfolios exclude CHF due to data limitations.[15] All data on spot and forward FX rates, interest rate swaps, and FRAs are daily data obtained from Bloomberg using London closing rates. Our dataset begins in January 2003 and ends in December 2020. We divide our data into three periods based on potentially different regulatory environments facing the intermediaries: Pre-GFC, January 1, 2003 to June 30, 2007, GFC, July 1, 2007 to June 30, 2010, and Post-GFC, July 1, 2010 to December 31, 2020.[16]

Our main analysis focuses on the post-GFC period, which features a non-risk-weighted leverage ratio constraint under the Basel III regulatory environment. This stands in sharp contrast to the pre-GFC and GFC samples, during which bank capital constraints were largely based on risk and riskless short-term CIP arbitrages faced no capital charge. An important lesson from the GFC turmoil was that the ex-ante risk weights could inaccurately reflect risk, and in 2010 the non-risk-weighted leverage ratio requirement was drafted as an important pillar of Basel III. Since then, the Basel III regulations have been finalized and gradually implemented. Even before the final rules took effect, early compliance of Basel III was common among large banking organizations, as it takes time to re-organize complex business activities. Regulators and bank shareholders may also have taken Basel

[14]We began with the G10 currencies, and excluded the Norwegian Krona (NOK) and Swedish Krona (SEK) due to limited data availability on OIS rates and IBOR FRAs. We also exclude the New Zealand dollar (NZD) because the OIS floating leg for the NZD is not a market rate but rather an administered central bank policy rate, the Official Cash Rate (OFR). The OFR is not equal to the actual overnight rate in the financial market, which generally fluctuates 0.25% around the OFR.

[15]The CHF OIS reference was changed at the end of 2017 due to a lack of liquidity in the underlying market. OIS swaps on the new index are not liquid enough for the purposes of our analysis. For this reason, we present single currency-pair results with CHF through the end of 2017 but do not include CHF in our results based on portfolios.

[16]We focus on monthly returns in our main analysis, and hence the last trading date in our sample is November 30, 2020.

III regulatory metrics into account even before the regulations were formally implemented. In addition to the Basel III implementation, our post-GFC sample also features two major financial crises, the European debt crisis and the COVID-pandemic induced financial turmoil in March 2020. CIP deviations widened significantly during both crises.[17]

2.1 OIS-Based Spot Cross-Currency Bases

We first define the τ-month tenor OIS-based spot cross-currency basis vis-à-vis the USD. Let $R^{c}_{t,0,\tau}$ denote the annualized spot gross τ-month interest rate in foreign currency c available at time t, and let $R^{\$}_{t,0,\tau}$ denote the corresponding spot rate in U.S. dollars. The middle subscript "0" denotes a spot rate (as opposed to a forward rate). We express exchange rates in units of foreign currency per USD. That is, an increase in the spot exchange rate at time t, S_t, is a depreciation of the foreign currency and an appreciation of the USD. The τ-month forward exchange rate at time t is $F_{t,\tau}$.

Following convention (e.g. Du et al. (2018b)), we define the τ-month tenor spot cross-currency basis of foreign currency c vis-à-vis the USD as

$$X^{c,\$}_{t,0,\tau} = \frac{R^{\$}_{t,0,\tau}}{R^{c}_{t,0,\tau}} \left(\frac{F_{t,\tau}}{S_t} \right)^{\frac{12}{\tau}} - 1, \tag{6}$$

and the log version as $x^{c,\$}_{t,0,\tau} = \ln\left(1 + X^{c,\$}_{t,0,\tau}\right)$. This definition is identical to the one employed in our model, except that we now consider an arbitrary tenor τ and use annualized interest rates.

The classic CIP condition is that $x^{c,\$}_{t,0,\tau} = X^{c,\$}_{t,0,\tau} = 0$. If the cross-currency basis $x^{c,\$}_{t,0,\tau}$ is positive (negative), then the direct U.S. dollar interest rate, $R^{\$}_{t,0,\tau}$, is higher (lower) than the synthetic dollar interest rate constructed from the foreign currency bond and exchange rate

[17]See Section 3.5 for more discussion on sample splits of the post-GFC period.

transactions.

The CIP condition is a textbook no-arbitrage condition if the U.S. and foreign interest rates used in the analysis are risk-free interest rates. For our main analysis, we choose OIS rates as our proxy for risk-free interest rate. The OIS rate is the fixed rate of a fixed-for-floating interest rate swap in which the floating rate is an overnight unsecured rate.[18]

The OIS is a good proxy for the risk-free rate across maturities for several reasons. First, the OIS allows investors to lock in fixed borrowing and lending rates for a fixed maturity, by borrowing and lending at the nearly risk-free floating overnight rate each day over the duration of the contract. Second, the interest rate swaps themselves have very little counterparty risk, because there are no exchanges of principal, only exchanges of interest. These derivative contracts are also highly collateralized and in recently years have been centrally cleared in most major jurisdictions. Third, OIS swaps are generally very liquid and traded at a large range of granular maturities (unlike e.g. repo contracts).

Internet Appendix Figure A1 shows the three-month OIS-based cross-currency basis for the six sample currencies vis-à-vis the USD between January 2003 and December 2020. The three-month OIS basis was close to zero pre-GFC and deeply negative during the peak of the GFC. After the GFC, OIS-based CIP deviations persisted. Among our sample currencies, AUD has the most positive OIS basis, and JPY, CHF, and EUR have the most negative OIS bases. Internet Appendix Figure A2 shows three-month IBOR cross-currency bases, which follow similar patterns.

We define the spot cross-currency basis between two non-USD currencies c_1 and c_2 as the

[18]The list of overnight reference rates for the OIS and their day count conventions for the seven major currencies currencies we study can be found in Internet Appendix Table A1. For two currencies, the OIS rate is non-standard. For CAD, the overnight rate is a repo (secured) rate; for CHF the unsecured overnight rate had volumes so low that the OIS rate was changed to reference a secured rate in 2017.

difference in their respective log cross-currency basis vis-à-vis the USD,

$$x_{t,0,\tau}^{c_1,c_2} = x_{t,0,\tau}^{c_1,\$} - x_{t,0,\tau}^{c_2,\$}. \tag{7}$$

We use this definition, as opposed to directly constructing the cross-currency basis between c_1 and c_2, both because most trades in currency forwards involve a USD leg and to restrict our sample to US FX trading days on which the U.S. federal funds market is open.[19]

2.2 Forward Bases

We next define a forward-starting cross-currency basis. Trading a forward starting cross-currency basis allows an agent to lock-in the price of a cross-currency basis trade that will start in the future.

We define a forward-starting cross-currency basis using forward interest rates and FX forwards. Let $R_{t,h,\tau}^{c}$ be the h-month forward-starting annualized τ-month gross interest rate in currency c at time t, and let $R_{t,h,\tau}^{\$}$ be the equivalent rate in the USD. The forward-starting cross-currency basis of foreign currency c vis-à-vis the USD is

$$X_{t,h,\tau}^{c,\$} = \frac{R_{t,h,\tau}^{\$}}{R_{t,h,\tau}^{c}} \left(\frac{F_{t,h+\tau}}{F_{t,h}} \right)^{\frac{12}{\tau}} - 1, \tag{8}$$

and the log version is $x_{t,h,\tau}^{c,\$} = \ln\left(1 + X_{t,h,\tau}^{c,\$}\right)$. Figure 1 illustrates the definitions of the spot and forward cross-currency basis.

Equivalently, we can define the log h-month forward τ-month cross currency basis at time

[19] According to recent BIS FX derivatives statistics, 90% of global FX swaps have the USD on one leg. Some cross pairs, such as EURJPY and EURCHF, are actively traded. There are only negligible differences between the cross-currency basis calculated directly using the FX swap rates for the cross pairs and the basis calculated using Equation (7). The triangular arbitrage for the cross-currency basis holds quite well post-GFC because the arbitrage only involves trading FX derivatives with limited balance sheet implications.

t in terms of two spot cross-currency bases under the assumption of no-arbitrage between forward interest rate swaps and the term structure of spot interest rate swaps:

$$x_{t,h,\tau}^{c,\$} = \frac{h+\tau}{\tau} x_{t,0,h+\tau}^{c,\$} - \frac{h}{\tau} x_{t,0,h}^{c,\$}. \tag{9}$$

The equivalence between Equations (8) and (9) is shown in Internet Appendix C. Equation (9) also shows that there is a close analogy between forward cross-currency bases and forward interest rates. As in Equation (7), we define the forward cross-currency basis between non-USD currencies c_1 and c_2 as

$$x_{t,h,\tau}^{c_1,c_2} = x_{t,h,\tau}^{c_1,\$} - x_{t,h,\tau}^{c_2,\$}. \tag{10}$$

We next consider the typical shape of the term structure of CIP violations – that is, the shape of the cross-currency basis forward curve. It is possible to construct forward CIP trades of many different horizons h and tenors τ. However, the most liquid and reliable OIS tenors are 1M, 2M, 3M, 4M, 6M, 9M, and 12M. In Figure 2, we present the forward curves of AUD and JPY vis-à-vis the USD for all reliable horizons: spot, 1M, 2M, 3M, 4M, 6M, and 9M. The tenor τ of these forward CIP trades differs, beginning at one month and increasing to three months. Internet Appendix Figure A3 presents an alternative version of the forward curve that uses only three month tenors.

We present these forward basis curves as time series averages for two currencies, AUD and JPY. These two currencies stand out in the data as having very positive/negative spot cross-currency bases vis-à-vis the USD during our post-GFC sample period, respectively. For each currency, we divide our sample into three sub-samples based on the tercile of the level of the spot 3M tenor basis. We then compute the time-series average of the spot and forward-starting cross-currency basis within each sub-sample.

From these forward curves, it is immediately apparent that the forward cross-currency bases tend to be larger (more positive) than the spot cross-currency basis for AUD, and smaller (more negative) for JPY. This fact is somewhat analogous to the tendency of the term-structure of interest rates to be upward sloping. If we think of forward cross-currency bases as being equal to expectations under a risk-neutral measure (an approach that is valid in our model despite the presence of arbitrage), then this suggests that the absolute value of spot cross-currency basis is generally expected to increase under the risk-neutral measure.

This raises the question of whether the spot cross-currency basis is also expected to increase in absolute value under the physical measure. That is, do the slopes of these forward curves reflect expectations, risk premia, or some combination thereof?

2.3 Forward CIP Trading Strategy

The forward CIP trading strategy consists of a forward cross-currency basis trade and a spot cross-currency basis trade at a later date. At time t, an agent enters into the h-month forward τ-month cross-currency basis trade. After h months, at time $t+h$, the agent unwinds the trade by shorting the then-spot τ-month cross-currency basis.

Although the forward CIP trading strategy involves two potential arbitrage opportunities, it is itself risky in that the spot τ-month cross currency basis at time $t+h$ is not guaranteed to be equal to the h-month forward τ-month cross-currency basis at time t. Figure 3 illustrates the mechanics this trading strategy.

The profits from this trading strategy are primarily a function of the realized cross-currency basis at time $t+h$ compared to τ-month forward cross-currency basis at time t. To first-order, the annualized profit per dollar notional (which can be thought of as an excess return) is

$$\pi^{c_1,c_2}_{t+h,h,\tau} \approx \frac{\tau}{h}(x^{c_1,c_2}_{t,h,\tau} - x^{c_1,c_2}_{t+h,0,\tau}). \tag{11}$$

The term $\frac{\tau}{h}$ plays the role of a duration, converting the difference between the forward and realized basis, $x^{c_1,c_2}_{t,h,\tau} - x^{c_1,c_2}_{t+h,0,\tau}$, into an annualized dollar profit per unit notional.[20]

The key property of the forward CIP trading strategy for our purposes is that it allows an intermediary to bet on whether the cross-currency basis will be higher or lower than implied by the forward cross-currency basis. Our model equates the magnitude of the basis with the degree to which regulatory constraints binds. Consequently, this strategy allows intermediaries to bet on whether constraints will be tighter or looser in the future.

The forward CIP trading strategy is a valid trading strategy even if the underlying cross-currency basis is not actually tradable or not a pure arbitrage. For example, individual arbitrageurs may not have direct access to the OIS floating leg.[21] Nevertheless, the forward CIP trading strategy is a valid trading strategy that bets on whether the basis as measured by OIS swaps referencing this rate becomes larger or smaller.

Moreover, the forward CIP trading strategy per se does not materially contribute to the balance sheet constraints of financial intermediaries, especially in comparison with the spot CIP arbitrage. This is because interest rate forwards and FX derivatives have zero value at inception. The required initial and variation margins for the derivative positions are generally a few percent of the total notional of the trade. In contrast, the spot CIP arbitrage requires actual cash market borrowing and lending, and is therefore balance sheet intensive.[22]

[20] We derive this expression, which is a first-order approximation, from a more exact calculation in Internet Appendix Section D.

[21] In the United States, the floating leg of the OIS is the federal funds rate. Only banks with reserve accounts at the Federal Reserve can trade in the federal funds market.

[22] For example, a $100 million spot CIP trade requires borrowing $100 million in the cash market and

2.4 Forward CIP Returns During Financial Turmoil

In the next section, we study the average returns of forward CIP trading strategies in various currencies and portfolios of currencies. To understand the patterns in the data behind our results, it is useful to first understand when the trading strategy does particularly well and particularly poorly. To highlight these patterns, we focus our discussion on the AUD-JPY currency pair (which is representative of other portfolios to be discussed in the next section), and on three distress periods in our data sample: the 2008-2009 GFC, the European debt crisis during 2011-12, and the COVID-19 induced turmoil in March 2020.

We begin with the events of March 2020. By March 19th, 2020 (roughly the peak of the financial turmoil), spot CIP bases widened to levels seen in prior crises in almost all currencies. The OIS-based AUD-JPY 3M spot basis reached 222 basis points, and this spike was not anticipated by the forwards. As a result, the profit per dollar notional of the 1M-forward 3M AUD-JPY forward CIP trading strategy (defined in equation (11)) was on average -103 basis points for trades initiated in the thirty days prior to March 19, 2020.

However, in April 2020 the spot bases converged back to roughly the levels observed in February 2020, and this normalization was also not fully anticipated by the forwards.[23] As a result of these movements, the 1M-forward 3M AUD-JPY forward CIP trading strategy experienced large positive profits, 189 basis points on average, on trades initiated in the

lending \$100 million in the FX swap market, which expends the size of the total exposure of the bank by \$100 million for the leverage ratio calculation. However, the impact of \$100 million interest rate swap on the leverage ratio is significantly smaller. The total exposure includes initial and variation margins (typically a couple percent of total notional), and an additional 0-1.5% of the swap notional calculated for off-balance-sheet interest rate derivative exposure using the Current Exposure Method, depending on the maturity of the interest rate swaps (Haynes et al. (2018)).

[23]On March 19, 2020, the 1M-forward 3M basis was 107 basis points. Thus, in contrast to the usual upward-sloping pattern, at the peak of the crisis the forwards anticipated a substantial decline in the spot basis. The realized decline, however, was even larger than what was priced in, by April 21st, 2020, the spot basis was back to 56 basis points and the 1M-forward basis was 61 basis points (returning to the usual upward-sloping pattern).

thirty days following March 19, 2020.

We observe similar patterns during other periods of financial turmoil. Trades initiated in the thirty days prior to September 15, 2008 (the bankruptcy of Lehman Brothers) lost on average 290 basis points, and trades initiated in the subsequent thirty days gained on average 189 basis points. Similarly, trades initiated in the month before November 21, 2011 (roughly the peak of the European debt crisis, although this is hard to date precisely) lost on average 29 basis points, and traded initiated in the subsequent thirty days gained on average 63 basis points.

In summary, our strategy experiences its largest losses on trades initiated right before the peak of financial turmoil, but experiences its largest gains on trades initiated in the immediate aftermath of that peak. We view these patterns as consistent with our interpretation that the forward CIP trading strategy returns capture unexpected tightening or loosening of financial constraints.

3 Forward CIP Trading Strategy's Excess Returns

In this section, we present evidence that the forward CIP trading strategy is profitable on average. The excess returns are observed in certain individual currencies against the USD, in trades between cross-currency pairs, and in portfolios. We find that the currency pairs with the highest excess returns are the currency pairs associated with the "FX carry trade." These currency pairs have high interest rate differentials, large CIP violations, and unhedged currency returns that are positively correlated with returns on the S&P 500 index. We also study a one-day forward CIP arbitrage to examine balance sheet constraints on quarter-end regulatory reporting dates.

3.1 USD-based Currency Pairs

We begin by discussing results for individual currencies. Panel A of Table 1 reports the profits per dollar notional on the one-month-forward three-month tenor forward CIP trading strategy in each of the six sample currencies vis-a-vis the USD. For each forward CIP trading strategy, we present the annualized mean profit per dollar notional and the Sharpe ratio, by period. Standard errors of the statistics are reported in parentheses.[24]

Beginning with the pre-GFC period, we observe that for all sample currencies vis-à-vis the USD, the pre-GFC profits are very close zero. Post-GFC, the profits in most currencies are larger in absolute value. Some currencies such as JPY have marginally statistically significant Sharpe ratios in the pre-GFC period, but this reflects small mean profits and even smaller standard deviations. In contrast, post-GFC, four currencies vis-à-vis USD have non-trivial mean profits and both statistically and economically significant Sharpe ratios.

Panel B of Table 1 illustrates that the sign of a currency's forward CIP trading profits (vis-à-vis the USD) is related to a number of other economically important properties of the currency. AUD, CAD, and GBP have positive forward CIP arbitrage profits, while EUR, CHF, and JPY have negative forward CIP arbitrage profits. We define the "investment" and "funding" currency based on the average interest rate of the foreign currency vis-à-vis the U.S. dollar in our sample, consistent with the standard FX carry trade literature, such as in Lustig and Verdelhan (2007); Lustig et al. (2011). The former group (AUD, CAD, and GBP) are high-interest-rate "investing currencies" and the latter group (EUR, CHF, and

[24] Means and Sharpe ratios are calculated using overlapping monthly profits per dollar notional from daily data and then scaled up by 12 and $\sqrt{12}$, respectively. We use Newey-West standard errors and the Newey and West (1994) bandwidth selection procedure, and use the "delta" method to compute standard errors for the Sharpe ratios (Lo, 2002). Internet Appendix Table A7 presents for robustness virtually identical results for portfolios (Table 3 below) using non-overlapping monthly data.

JPY) are low-interest-rate "funding currencies" for the unhedged FX carry trade.[25] In bad times (proxied by low S&P 500 returns), the "funding currencies" tend to appreciate against the USD, while the "investing currencies" depreciate. CIP deviations make "funding currencies" more appealing in terms of their synthetic dollar interest rates. These currencies have substantial negative cross-currency bases (higher synthetic dollar interest rates), whereas "investing currencies" have less negative or even positive cross-currency bases vis-à-vis USD.

Moreover, the AUD, CAD, and GBP all have an upward-sloping CIP term structure on average.[26] In contrast, EUR, CHF, and JPY have a downward-sloping CIP term structure on average. Put another way, the increases in the absolute value of the basis implied by the forward curves do not actually occur, on average. This result is analogous to the existence of the term premium in the term structure literature.[27]

As mentioned in Section 1, OIS rates are not directly comparable across currencies. For example, the CAD OIS rate is collateralized, whereas most other rates are not. As another example, the CHF OIS rate changed by around 20 bps as part of an overnight benchmark rate reform in 2017. If we used the new index instead of the old index to compute the spot basis, the CHF-USD basis would be less negative by about 20 bps.[28] In USD, institutional factors cause the OIS rate (fed funds) to fall below the rate on excess reserves (Bech and Klee (2011)), whereas the EONIA rate generally exceeds the ECB deposit rate. For these reasons,

[25] We group GBP with "investment" currencies, even though the average GBP interest rate is slightly below the U.S. rate in the post-GFC sample, because GBP interest rates are generally higher than U.S. interest rates over longer samples (e.g. post-2000). The low average GBP interest rate in the recent sample is driven primarily by low rates in the post-Brexit period.

[26] We define slope as the difference between the 1-month forward 3-month basis and the spot 3-month basis.

[27] Taking this analogy further, Internet Appendix E provides suggestive evidence that the slope of the forward curve predicts forward CIP trading profits, just as the slope of the term structure predicts bond returns (Campbell and Shiller, 1991). However, the statistical significance is sensitive to the inclusion of the COVID-19 crisis period in the sample.

[28] As mentioned previously, swaps on the new CHF OIS index are not liquid enough for our purposes, which is why we present results with the old index.

we do not view (for example) the sign of the CAD-USD basis or the exact ranking of the bases in B of Table 1 as particularly meaningful. Instead, we note that the investing currencies and funding currencies are notably different across all five of the dimensions considered in Panel B of Table 1.

3.2 Currency Pairs with the Largest Bases

Our model suggests that intermediaries will actively trade the bases with the maximal arbitrage per unit risk weight. If risk weights are roughly equal across currencies, this suggests focusing on the currency pairs with the largest bases. As discussed earlier ("Heterogeneity Across Currencies" in Section 1), for a variety of reasons we do not take a stand on which currency pair truly has the largest basis but instead present results for the ten currency pairs with the largest bases. In the context of our model, if intermediaries actively trade all of these bases, the differences in the magnitude of the basis across pairs must be due either to measurement issues or differences in risk weights. In both of these cases, we would expect positive expected returns and Sharpe ratios from our forward arbitrage strategy for all ten bases.[29]

In Table 2, we present the forward CIP returns associated with the ten currency pairs with the largest average spot 3-month bases post-GFC.[30] The mean returns of these currency pairs are linear combinations of the mean returns for each currency leg vis-à-vis USD presented earlier; the Sharpe ratios are not. The mean average profits are positive for all ten pairs post-GFC, and the annualized Sharpe ratio is above 0.5 for 8 out of 10 currency pairs. The

[29]If each of the ten forward arbitrage strategies were an exact (noiseless) bet on the size of the shadow cost λ_{t+1}^{RC}, scaled by the risk weight k^i, they would all have positive expected returns and the same Sharpe ratios. In the presence of currency-specific noise, the Sharpe ratio will be attenuated for each currency pair based on the magnitude of the noise.

[30]These ten pairs also all have a positive spot 3M basis on virtually every day in our sample.

average interest rate differential for each of these ten pairs is positive, once again suggesting a relationship between carry and the profits of the forward CIP trading strategy.

Consider as an example the "classic carry" currency pair of long AUD, short JPY. This pair has one of the largest spot bases, and is particularly associated with the carry trade.[31] The AUD-JPY forward CIP trading strategy earns an a post-GFC average profit equal to 16 basis points and its annualized Sharpe ratio is 1.18. Both results are highly statistically significant, and the magnitude of the Sharpe ratio is high compared to many documented trading strategy returns in the literature. For comparison, the traditional un-hedged FX carry trade has an annualized Sharpe ratio of 0.48 for developed market currencies from 1987 to 2009, and the annualized Sharpe ratio of a value-weighted portfolio of all U.S. stocks from 1976 to 2010 is 0.42 (Burnside et al. (2010), Burnside et al. (2011)). Note, however, that our analysis is limited to the post-GFC period, which is a short sample. During this period, the developed market carry trade and U.S. stock portfolio had annualized Sharpe ratios (0.18 and 1.05, respectively) that are not representative of the longer sample.[32]

The connection between interest rate differentials and the spot cross-currency basis was documented in Du et al. (2018b). As discussed in the survey of Du and Schreger (2021), CIP deviations are induced by the interaction between steady demand for funding and hedging services and intermediary constraints. The funding and hedging demand for high-interest-rate currencies is particularly strong from low-interest-rate countries, as the search-for-yield investors demand assets denominated in high-interest-rate currencies. One implication of that story, through the lens of our model, is that the risk that the classic carry basis becomes

[31] AUD-CHF has a slightly larger average spot basis than AUD-JPY. However, as mentioned previously, there are significant problems with the CHF OIS index and our CHF sample ends in 2017.

[32] That said, the correlation of the AUD-JPY forward CIP return to the U.S. market is not very high (about 0.3 monthly post-GFC), so there is no particular reason to think that whatever forces caused the market to have high returns post-GFC also influenced the forward CIP return.

larger is priced because it correlates with intermediary constraints more broadly. Consistent with this, our results show that there is a relationship between the spot basis, interest rate differentials, and forward CIP trading profits.

3.3 Portfolios of Forward CIP Trading Strategies

In addition to the "classic carry" AUD-JPY currency pair, we examine five portfolios of forward CIP trading profits: "dollar-neutral carry", "dynamic top-five basis", "static top-six basis", "top-six first PC", and "dollar". The first four of these are based on interest rate differentials and the size of the spot cross-currency basis; they generate positive mean returns and high Sharpe ratios post-GFC. In contrast, the return for the dollar portfolio is insignificant. As mentioned previously, all of these portfolios exclude CHF due to data limitations.

The portfolios are defined as follows. The "dollar-neutral carry" portfolio is a dollar-neutral carry strategy. The portfolio goes long in the forward CIP trading strategy for the AUD, CAD, and GBP vis-à-vis the USD, each with 1/3 weight, and short in the forward CIP trading strategy for the EUR and JPY vis-à-vis the USD, each with 1/2 weight. The "dynamic top-five basis" portfolio equally weights the forward CIP trading strategies for the largest five spot cross-currency basis pairs and is re-balanced monthly. The "static top-six basis" portfolio equally weights the forward CIP trading strategies in the six non-CHF currency pairs listed in Table 2, which were selected based on the average spot 3-month cross-currency basis in the post-GFC sample. The "top-six first PC" portfolio is the first principal component of those same six pairs. The sign and scale of the first PC (which are arbitrary) are chosen to match the volatility of the AUD-JPY currency pair and to ensure a positive correlation between the first PC and AUD-JPY.[33] The "dollar" portfolio places equal weights on each of the individual non-CHF sample currencies vis-à-vis the USD. All of these portfolios, with the exception of the dollar portfolio, are have highly correlated returns (the lowest pairwise correlation is 0.93 in our non-overlapping monthly sample).

We report the annualized mean profit and the Sharpe ratio for these five portfolios, together with the performance for the "classic carry" strategy in Table 3. The pre-GFC mean profits of these portfolios are all close to zero. The post-GFC mean profits are significantly positive at about 11 to 16 basis points for all of the portfolios except the "dollar" portfolio, with significant annualized Sharpe ratios between 1 and 1.3. In contrast, the post-GFC profits and the Sharpe ratio for the "dollar" portfolio remain close to zero. In robustness checks, we show similar patterns hold for one-month tenors, three-month horizons, and for strategies based on IBOR bases (Internet Appendix Tables A3, A4, A5, and A6).[34]

3.4 Quarter-Ends

Quarter-ends offer an interesting window to examine forward CIP deviations and the profits of our forward trading strategy. As documented in Du et al. (2018b), there are large spikes in short-term CIP deviations for contracts that cross the quarter-ends. Those authors attribute the quarter-end spikes to the fact that the Basel III leverage ratio is calculated using quarter-

[33]The weights are roughly AUD-JPY 0.26, AUD-EUR 0.16, USD-JPY 0.27, CAD-JPY 0.22, USD-EUR 0.17, GBP-JPY 0.18. The sum of the weights exceeds one because AUD-JPY is more volatile than most other currency pairs; matching the volatility of AUD-JPY facilitates a comparison between results with the PC1 and results with AUD-JPY. We have constructed versions that use weights based on the first principal component of the spot bases, as opposed to of the forward CIP returns, as well as versions that use all pairwise combinations of forward CIP returns, and not just the six listed in Table 2. The resulting portfolios have virtually identical returns. The "dynamic top-five" portfolio is tradable as it is formed based on ex-ante available interest rate information, whereas the "static top-six basis" and "top-six first PC" are constructed using the full sample. The choice of five vs. six pairs is arbitrary and has minimal impact on the results.

[34]Our IBOR data has missing data in CAD but not CHF; as a result, our IBOR portfolios differ from our OIS portfolios because they include CHF but not CAD.

end snapshots of bank balance sheets in many non-U.S. jurisdictions, tightening leverage constraints for intermediaries on quarter-ends. We show that there is additional premium in our forward trading strategy associated with the quarter-end turn. To the extent that the quarter-end effect in the spot CIP deviation offers clean evidence on the effects of leverage constraints, our finding of a positive risk premium associated with the quarter-end turn offers additional support for the idea that leverage constraints are priced.

We have thus far side-stepped the issue of quarter-ends in our analysis by studying forward CIP trading strategies with a three-month tenor, ensuring that the contracts in question always cross quarter-end. In this subsection, we instead study a forward CIP trading strategy that uses tenors of a single business day and focus on quarter-end effects. One advantage of examining one-day forward trading strategy is that we have many more non-overlapping daily observations to calculate the mean returns over the post-GFC sample.

We follow Correa et al. (2020) and construct overnight (ON) and tomorrow/next (TN) CIP deviations. These are constructed from central bank deposit rates as opposed to OIS rates. The ON CIP deviation is a one day spot CIP violation; the TN CIP deviation is a one-day-forward-starting one-day CIP violation. From these, we can construct a one-day forward CIP trading strategy by betting on whether the TN CIP deviation traded at time t is larger than the subsequent realized spot ON CIP deviation traded at $t + 1$. We provide details on ON and TN basis calculations in Internet Appendix F.

In Table 5, we regress the annualized ON CIP deviation, one-day lagged TN CIP deviation, and the profit on the one-day forward CIP trade on a constant and quarter-end dummy, pooled across the funding currencies (CHF, EUR and JPY) vis-à-vis the USD.[35] Column 1

[35] Because of our limited sample of quarter-ends, pooling across currencies is necessary to precisely estimate quarter-end effects. We focus on the funding currencies vis-à-vis the USD because of data availability and the relationship between forward CIP returns and the carry trade documented thus far. Using central bank deposit rates allows us to include CHF.

shows that the ON basis averages to 11 basis points and jumps by 154 basis points on average when crossing quarter-ends. Column 2 shows that the TN basis averages to 15 basis points and jumps by 207 basis points on average one (business) day before the quarter-ends. The large jump in the TN basis right before quarter-ends suggests that the quarter-end effects are anticipated and in part priced into forward CIP deviations. Since the average TN basis is higher than the average ON basis and the quarter-end jump in the TN premium is on average larger than ON premium, there is a positive average profit for our one-day forward CIP trading strategy and an additional positive risk premium crossing the quarter-ends. In Column 3, we can see that the average profit on the ON-TN forward CIP trading strategy outside is about 4 basis points, and about 53 basis points higher on quarter-ends.

In Internet Appendix Figure A4, we show the shape of the forward curve of the 1M-tenor AUD-JPY basis with three sub-samples based on whether the next quarter-end is within the next month, between one and two months in the future, or more than two months in the future. We observe that all three lines exhibit a spike, precisely when the interest tenor in the basis crosses the quarter end. This further illustrates that intermediary's quarter-end constraints are anticipated and priced. However, we cannot detect additional risk premium for the 1M-tenor forward associated with quarter-end crossings in Internet Appendix Table A12, likely due to limited power when using the longer-tenor contracts in detecting the risk premium associated with quarter-ends.

3.5 Additional Sub-sample Analysis and Transaction Costs

COVID-19. Our sub-sample analysis in Table 4 presents results with and without the market turmoil induced by the COVID-19 pandemic. The average returns of our portfolios are similar in the two sub-samples.

As discussed in subsection 2.4, the AUD-JPY forward CIP trading strategy experienced large losses at the onset of the pandemic, and subsequently experienced large gains as the turmoil subsided. In total, the trading strategy earned roughly average profits during 2020 relative to previous years, despite the COVID-19 crisis. A similar pattern appears for other portfolios: the large losses incurred on trades initiated in February 2020 were offset by large gains over the next few months, and the overall returns for 2020 are similar to the average of prior years. The Sharpe ratios for the sample including 2020 are slightly lower than the sample ending in 2019 due to the higher volatility of returns in 2020.

Consistent with the idea that CIP violations measure the tightness of constraints, our strategy experiences negative profits at the beginning of financial stress. However, during periods of financial stress, the risk premia earned by our strategy are particularly large, which is to say that the risk that constraints tighten further carries a large price during these episodes. As a result, sample periods that include both the onset and resolution of financial stress have an ambiguous effect on the average returns of our strategy.

Basel III. Our post-GFC sample begins in 2010, which marks the beginning of the lengthy process for the introduction and implementation of Basel III banking regulations. These regulations substantially affected banks ability to engage in balance-sheet intensive activities.[36] Notably, the public disclosure of the Basel III leverage ratio starts on January 1, 2015. Given that the leverage ratio requirement under Basel III is the most relevant regulatory constraint for CIP arbitrage, we split the post-GFC period into pre- and post-2015. Internet Appendix Table A8 shows that our main results are robust in both sub-samples post-GFC, with mean

[36]Besides CIP deviations, higher balance sheet costs are also manifested in the repo market. In Internet Appendix Figure A5, we show that the average gross repo position of primary dealers declined by more than 40% in the post-GFC sample compared to their pre-GFC peak, which is consistent with more binding non-risk-weighted leverage constraints. The spread between large banks' lending rate and borrowing rate in repo markets also widened significantly post-GFC.

returns that are perhaps slightly larger in the post-2015 sub-sample. The Sharpe ratios in the post-2015 sample are smaller due to the effects of the COVID-19 crisis discussed above.

Transactions Costs. We have limited data on the transactions costs associated with implementing the forward CIP trading strategy. Large intermediaries are likely to implement the strategy at low cost (either collecting the bid-offer when trading with clients or trading at close to the mid-price in inter-dealer transactions). Anecdotal evidence suggests that some large hedge funds use interest rate and FX derivatives to arbitrage the term structure of CIP violations, suggesting that the transaction costs are not prohibitively large.

We study these forward CIP trading strategies because they reveal interesting information about currencies and intermediaries, and not because we advocate them as an investment strategy. It may well be the case that a typical trader in a small hedge fund paying the bid-offer on the various instruments used to implement the trading strategy would not find it profitable. We provide a conservative estimate of transaction costs by assuming the full quoted bid-offer spreads from Bloomberg are paid on every single instrument involved in the trading strategy. Note this approach likely substantially overstates total transaction costs as our trade can be easily structured as an asset package. Taking the USD-JPY OIS trade as an example, the annualized transaction costs based on full Bloomberg bid-offer spreads are almost three times the size of the annualized profit for the one-month horizon forward trade and roughly equal to the profit for the three-month horizon forward trade (Internet Appendix Table A13).

4 Implications for the Price of Risk

In the preceding section, we found that there is a substantial risk premium associated with the risk that AUD-JPY and other bases become larger. We interpret this, through the lens of our model, as implying that this basis is a measure of intermediary constraints and that the risk that intermediary constraints tighten is a priced risk factor.

This interpretation has several implications that we explore in this section. First, it suggests that the level of the spot CIP basis should be correlated with other arbitrages affected by constraints on intermediaries. Second, it suggests that the basis should be correlated with measure of intermediary wealth and other measures of intermediary constraints. Third, it implies (assuming an intertemporal hedging motive) that the forward CIP risk premium should exist even after controlling for intermediary wealth, and that the forward CIP return should be included along with intermediary wealth in the SDF. Fourth, the forward CIP risk premium should be consistent with the prices of risk extracted from other assets that intermediaries trade. We explore each of these implications in turn.

4.1 CIP vs. Other Arbitrages

We interpret the AUD-JPY basis and other CIP deviations as measures of intermediary constraints. However, our model implies that intermediary constraints, if present, should affect many no-arbitrage relationships and not just CIP. To verify that the bases we study are indeed measures of intermediary constraints, we begin by confirming that they co-move with other documented near-arbitrages. Specifically, we show that the AUD-JPY cross-currency basis co-moves with the first principal component of other near-arbitrages from outside the FX market.

We consider seven types of near-arbitrages: the bond-CDS basis, the CDS-CDX basis, the USD Libor tenor basis, 30-year swap spreads, the Refco-Treasury spread, the KfW-Bund spread, and the asset-swapped TIPS/Treasury spread. These near-arbitrages have been examined in recent literature, such as Bai and Collin-Dufresne (2019); Boyarchenko et al. (2018); Fleckenstein et al. (2014); Jermann (2019); Longstaff (2002); Schwarz (2018). We describe these near-arbitrages in more detail in Internet Appendix G.

Each of these near-arbitrages is subject to measurement errors and idiosyncratic supply and demand shocks. We use a principal component analysis to extract the common component. Our model implies that variation in the balance sheet capacity of financial intermediaries should affect all these near-arbitrages, and we therefore view this common component as an alternative measure of intermediary constraints.

We show in Figure 4 that our benchmark AUD-JPY cross-currency basis and the first principal component (PC) of the other near-arbitrages follow broadly similar trends. We find that the first PC explains 51% of total variation in the level of the seven near-arbitrages between January 2005 and December 2020, and has a 41% correlation with the level of the AUD-JPY cross-currency basis post-GFC.[37]

However, CIP deviations have several advantages over these other near-arbitrages. First, they are close to true arbitrages, unlike some of these other measures. For example, the Libor tenor basis and Treasury swap spread may reflect credit risk rather than intermediary constraints, while the bond-CDS basis has a cheapest-to-deliver option and other complications. Second, they are precisely measured, exhibiting less high frequency volatility than most of these other measures. Third, and most importantly for our empirical strategy, they have a rich term structure that allows us to construct our forward CIP trading strategy.

[37] All seven near-arbitrages are long-term (five years or above), while the cross-currency basis we use has a three-month tenor, so the correlation between the two series should not be perfect.

For these reasons, we use CIP violations as our as our preferred measure of intermediary constraints.

4.2 CIP vs. Existing Measures of Intermediary Constraints

If the cross-currency basis measures intermediary constraints, then the general equilibrium models of He and Krishnamurthy (2011) and Kondor and Vayanos (2019) imply that it should co-move with intermediary net worth. However, demand and regulatory shocks should also affect the tightness of intermediary constraints, so we do not expect a perfect correlation. Similarly, Adrian et al. (2014) argue for broker-dealer leverage as an alternative measure of intermediary constraints. Of course, if broker dealers are subject to leverage constraints, the tightness of those constraints might change without leverage changing (for example, in response to changing investment opportunities). Again, for this reason, we do not expect a perfect correlation between our measure of the tightness of intermediary constraints and broker-dealer leverage.

We explore the relationship between existing intermediary constraint measures and the AUD-JPY cross-currency basis in Figure 5. We use as our primary measure of intermediary wealth the intermediary equity value of He et al. (2017) (henceforth HKM), which is the cumulative return of value-weighted equity of primary dealers. We also consider, following He et al. (2017), the equity capitalization ratio of the dealers (HKM Capital Ratio) and the broker-dealer leverage ratio used in Adrian et al. (2014) (defined as broker dealer book asset over book equity).

In Figure 5, we present a time series of the spot 3M AUD-JPY basis and these intermediary wealth and constraint measures. The cross-currency basis and the proxies for intermediary wealth measures appear to be (negatively) correlated. This suggests that variations in the spot basis are in part driven by shocks to intermediary wealth. However, in recent years, we observe an upward trend in the basis, likely attributable to changes in regulation (e.g. the implementation of Basel III). During this period, intermediary wealth also increases. As discussed earlier, we expect the basis to capture regulatory and demand shocks in addition to changes to intermediary wealth. The widening of the CIP deviations post-GFC lines up with a decline in the broker-dealer leverage, consistent with the idea that both variables capture intermediary constraints.

4.3 The Basis and the SDF

Can the correlation between CIP violations and intermediary equity returns explain the risk premia we documented in the previous section? If the intermediary's SDF consisted only of the intermediary wealth return, then regressions of excess asset returns on proxies for this factor should generate intercepts of zero (Cochrane (2009)). In the analysis that follows, instead of focusing on one particular forward CIP trading strategy, we focus on the first principal component portfolio ("Top-Six First PC") described in the previous section.[38]

Table 6 reports these regressions for four configurations (columns (2) through (5)) of intermediary wealth return proxies: Market only, Intermediary Equity only, Market and Intermediary Equity, and Market and HKM Factor. Here, Market and Intermediary Equity refer to the return on the stock market and the value-weighted equity of primary dealers, respectively, and HKM Factor refers to innovations to the AR(1) process of primary dealers' equity capital ratio, as defined in He et al. (2017). The outcome variable is the profits of the 1M-forward 3M-tenor "Top-Six First PC" forward CIP trading strategy, scaled by 1/3 to convert the units from annualized profits per dollar notional to bps per month (see Equation

[38]Prior versions of this paper instead focused on AUD-JPY and obtained qualitatively similar results: the two portfolios are 97% correlated in the post-GFC period.

(11)).

All four configurations generate statistically significant intercepts ("α"), rejecting the null that the HKM wealth-portfolio factors are sufficient to explain the risk premia on the forward CIP trading strategy. Moreover, the point estimates for the intercepts range from 3.6 to 4.5 bps per month when using non-overlapping monthly data, which is close to the average excess return of 5.0 bps/month (see column (1)). That is, proxies for intermediary wealth returns explain only a small part of the excess returns associated with the forward CIP trading strategy. Column (7) presents a quarterly regression that uses the Market and AEM broker-dealer leverage factor as proxies for intermediary wealth and constraints. We again find that the forward CIP return's exposure to the Market and AEM factor does not explain the bulk of its excess returns; however, with only 42 quarterly data points, this result is substantially noisier.

These results suggests that SDFs which include both intermediary wealth returns and forward CIP returns (as in Equation (1)) should fit the data better than SDFs that use only intermediary wealth. The Bayesian approach of Chib et al. (2020) (which corrects the approach of Barillas and Shanken (2018)) provides a method of comparing SDFs to formalize this intuition. We consider three sets of possible SDFs: (1) combinations of the market, intermediary equity return, and forward CIP return, (2) combinations of the market, HKM factor, and forward CIP return, and (3) combinations of the AEM leverage factor, market, and forward CIP return. The second and third sets of SDFs always include the non-tradable HKM and AEM factors in the SDF. In Panel B of Table 6, for each of these groups of SDFs, we calculate the posterior probabilities (given our data and the prior over models described by Chib et al. (2020)) for each SDF. The total posterior probabilities of models that do and do not include the forward CIP return are presented in the rightmost column. In the monthly data specifications, the models that include the forward CIP return have a total posterior probability that is substantially higher than models that do not include the forward CIP return. That is, the Chib et al. (2020) procedure recommends including the forward CIP return as a factor in the SDF. The quarterly data sample is insufficient to distinguish between models that do and do not include the forward CIP return.

We would caution readers, however, that the exact level of the posterior probabilities can be sensitive to changes in the sample period or variables in question. The probabilities associated with models featuring a forward CIP return are substantially higher when that forward CIP return is the AUD-JPY return as opposed to the "Top-Six First PC" portfolio, despite the high correlation between those two returns (see Internet Appendix Table A9). This difference is driven by the small differences in the mean return and in the correlation between those two returns and the Market portfolio. Likewise, the procedure's preference for models with the market return as opposed to the intermediary equity return is driven the high return on the market, but not intermediary equity, in the post-GFC period; the two have similar average returns over longer samples.

If the forward CIP return is part of the SDF, its mean return can help identify the coefficients of the SDF. By construction, the returns of our forward CIP trading strategy are also the (negative of) innovations to the magnitude of the cross-currency basis. Our "Top-Six First PC" forward CIP trading strategy earns 4.6 bps per month on average in the post-GFC period.[39] Take the Intermediary Equity return as the tradable proxy for intermediary wealth returns; the mean excess return of Intermediary Equity from 1970 to 2018 is 59 bps per month. Defining λ as the vector containing these mean excess returns, we can extract estimates of γ and ξ (the coefficients in the SDF of Equation (1)) by multiplying these

[39]This is the average of the daily sample of overlapping monthly returns. The non-overlapping monthly return sample has an average of 5.0 bps per month, as shown in column (1) of Table 6.

means by the inverse of the variance-covariance matrix (Σ) of the two factors (see Cochrane (2009)). We estimate the standard deviation of the "Top-Six First PC" forward CIP return at 14 bps per month, and the standard deviation of the Intermediary Equity return at 6.3% per month. The correlation between these two factors is 0.31 in our post-GFC sample, meaning that the bases with the largest magnitudes tend to shrink when intermediary equity returns are positive. Using these estimates, with GMM standard errors in parentheses,

$$\begin{bmatrix} \gamma \\ \xi \end{bmatrix} = \Sigma^{-1}\lambda = \begin{bmatrix} -0.2\ (1.5) \\ 247\ (63.0) \end{bmatrix}.$$

Our results are consistent with $\gamma < 1$ in two ways. First, our direct estimate of the γ parameter is less than one, and in fact essentially zero. Second, the sign of our estimate of ξ is greater than zero, which should be expected if $\gamma < 1$. The basic fact driving this result is that that exposure to the forward CIP return appears to explain essentially all of the excess returns on intermediary equity. As a result, our point estimates are consistent with the model that motivates Adrian et al. (2014), with risk-neutral but constrained intermediaries. However, these are point estimates and subject to estimation error; our estimate for ξ is statistically significant at the 1% level, but we cannot reject γ coefficients that exceed one. See Internet Appendix H for a discussion of the estimation and standard errors.

Our estimate of $\xi > 0$ (implying $\gamma < 1$) is driven by the fact that the forward CIP strategy achieves a risk premium that is larger than would be expected given its beta to the intermediary equity factor. Recall that a large basis indicates better future investment opportunities. Intermediaries will view exposure to basis shocks as risky if they prefer to hoard wealth to take advantage of those better investment opportunities, which occurs when $\gamma < 1$. We emphasize that this is not a quirk of our model, but rather a general fact about investment opportunities and intertemporal hedging.[40]

However, we cannot rule out the alternative possibility that the forward CIP return is a better proxy for the true intermediary wealth return. If the risk premia we document is caused entirely by this effect and not inter-temporal hedging, the forward CIP return must be a much better proxy for the true intermediary wealth return than the HKM intermediary equity measure. Suppose that $\gamma = 1$, so there is no intertemporal hedging concern. Our Sharpe ratio estimate for the "Top-Six First PC" forward CIP trading strategy implies (by the Hansen-Jagannathan bound) that the true intermediary wealth return must have an annual volatility of at least 100%, far higher than the annualized volatility of the Intermediary Equity return. Suppose instead that $\gamma > 1$. In this case, the intermediary manager should view the forward CIP trading strategy as not being very risky at all, because it offers low returns only when there are future arbitrage opportunities. To overcome this intertemporal hedging effect, we would have to suppose that our forward CIP trading returns are strongly correlated with the true intermediary wealth returns.[41]

We believe our results are interesting regardless of which of these interpretations is preferred. Either intertemporal hedging considerations are large and can be proxied for by the forward CIP return, or the forward CIP return is a better way of measuring intermediary wealth returns (the main component of the SDF). Under either of these interpretations, we would be justified in using the forward CIP return as an asset pricing factor.

[40]See, for example, pg. 1157 of Kondor and Vayanos (2019).

[41]Given the persistence of the cross-currency basis, which causes the intertemporal term to be large, it is not obvious that even perfect correlation with the intermediary wealth return solves the problem. However, without an exact quantification of the intertemporal terms, we cannot rule out this possibility.

4.4 Cross-sectional Asset Pricing

We next present a cross-sectional analysis, which provides an additional test of our theory. If the SDF in Equation (1) is correctly specified and the traded factors are good proxies of the true factors, the prices of risk estimated from the cross-section of asset returns should be the same as the unconditional risk premia of the traded factors.

We view this analysis as a complement to our earlier direct estimates of the forward arbitrage return. The key advantage our approach enjoys over other empirical intermediary asset pricing exercises is that we are able to directly estimate the price of the risk that constraints tighten. The cross-sectional exercise allows us to verify that the price of risk we directly estimate is consistent with the price of risk we infer from the cross-section. Because we are focused on the post-GFC sample, the power of our cross-sectional exercise is limited. Despite this limitation, we are in some cases (when pooling across asset classes) able to reject the hypothesis of a zero risk price but not the hypothesis that the risk price in the cross-section matches the risk price we directly estimate.

Our exercise builds directly on HKM. We study equities (FF6, the Fama-French 6 size by value portfolios, Fama and French (1993)), currencies (FX, developed and EM currencies sorted on forward premia, Lustig et al. (2011)), US bonds (US, six maturity-sorted CRSP "Fama Bond Portfolios" of Treasury bonds and five Bloomberg corporate bond indices), sovereign bonds (Sov, sorted on credit rating and beta to the market, Borri and Verdelhan (2015)), equity options (Opt, twelve portfolios of S&P 500 calls and puts, Constantinides et al. (2013)), credit default swap indices (CDS, five traded CDS indices), and commodities (Comm, six Bloomberg commodity futures return indices). We also study single-currency forward CIP returns with OIS and IBOR rates (FwdCIP).

Note that many of these test portfolios have a factor structure to their returns. For example, the currency portfolios of Lustig et al. (2011) can be summarized by the "carry" and "dollar" factors. Following HKM, we do not include these factors as additional factors in our model. That is, we are asking whether the risk premium associated with the carry trade is explained by its exposure to intermediary wealth and the forward CIP return, not whether the proposed factors of the SDF predict the part of currency returns that is not explained by the carry and dollar factors.

The conjecture we are testing, which follows from our hypothesized form of the stochastic discount factor,[42] is that

$$E[R_{t+1}^i - R_t^f] = \alpha + \beta_w^i \lambda_w + \beta_x^i \lambda_x, \tag{12}$$

where β_w^i is the beta of asset i to the intermediary wealth return and β_x^i is the beta to the negative of the forward CIP return. These betas can be estimated in the standard way using a time series regression,

$$R_{t+1}^i - R_t^f = \mu_i + \beta_w^i (R_{t+1}^w - R_t^f) + \beta_x^i r_{t+1}^{|x|} + \epsilon_{t+1}^i, \tag{13}$$

where $r_{t+1}^{|x|}$ is the negative of the return of the "Top-Six First PC" of forward CIP returns.[43]

Our preferred specification uses the Intermediary Equity return as our proxy for R_{t+1}^w. As discussed in Cochrane (2009), with tradable factors, if we included the factors as test assets and used GLS or two-step GMM to estimate the risk prices λ_x and λ_w, we would recover

[42] Our hypothesis is expressed as a linear form for the log SDF, but we test a linear SDF to stay closer to the procedure of He et al. (2017).

[43] Our model implies that the risk-free rate in this time-series regression is misspecified, and should include an adjustment proportional to x_t (see Internet Appendix Equation (A2)). However, because x_t has only a little ability to predict $R_{t+1}^w - R_t^f$ or $r_{t+1}^{|x|}$, omitting it has almost no effect our results. See Internet Appendix Table A22 for a version of Table 8 with a risk-free rate adjustment.

the mean excess returns of those factors. We ask instead whether the price of risk implied by the cross-section of other asset returns is consistent with the mean excess returns on our tradable factors. For this reason, we estimate Equation (12) as an OLS regression, with GMM standard errors to account for the estimation of the betas in Equation (13), following chapter 12 of Cochrane (2009).[44] Both regressions use monthly data. For each asset class, and for a combination of all eight asset classes, we report the "H1 p-value" from testing whether λ_w and λ_x are equal to the mean excess return of the corresponding factor (59 bps per month and -5.0 bps per month in our non-overlapping monthly sample, respectively). This p-value, as opposed to the usual test of whether the coefficients are zero, is the focus of our analysis.

One difference between our main specification and the textbook procedure is that the samples we use to estimate the betas and the mean excess returns are different. Our model argues that the cross-currency basis enters the SDF because it measures the degree to which regulatory constraints bind, a viewpoint relevant for the post-GFC period. Ten years of data, however, is generally too short to reliably determine whether one test portfolio has a higher expected return than another test portfolio. To overcome this difficulty, we estimate the cross-sectional regression using the longest available sample for each test portfolio, while estimating the betas using only the post-GFC sample. This approach increases the likelihood of rejecting our "H1" hypothesis (biasing against our main finding), and is valid if the long-sample expected excess returns are also the expected excess returns in the post-crises period. We present broadly similar results using only post-GFC data in the Internet Appendix Table A28.[45]

[44]More efficient (in an asymptotic sense) procedures estimate equations (12) and (13) jointly as moment conditions. These procedures have advantages and disadvantages relative to the cross-sectional approach; see Cochrane (2009).

[45] One difference between our main results and our results using post-GFC means is the risk price of the

There is the potential for weak identification in our setting. Weak identification arises when there is not significant cross-sectional variation in the betas of the test assets to the factors. Kleibergen and Zhan (2020) develop a "pre-test" that tests whether the estimated betas of the test assets are different from each other. We report the p-value associated with this test. Low p-values suggest rejection of the hypothesis that the betas are equal.[46] Note that the primary focus of our exercise is whether we can reject our "H1" hypothesis. Spurious rejection induced by weak identification makes it harder for us to find cross-sectional results that are consistent with our direct estimates of the risk premia for our tradable factors.

Note that our estimates depart in a variety of ways from HKM. Our results are estimated on monthly data, and our betas are estimated only in the post-GFC period. Our test portfolios in each asset class are also different, in some cases only slightly and in some cases more substantially. We describe these details in the Internet Appendix, Section K.

Our main cross-sectional results are shown in Table 8. These results use the two-factor specification of Equation (12), with the Intermediary Equity return as the empirical proxy for R^w_{t+1}. The first eight columns show results for individual asset classes. For several asset classes, we cannot reject the hypothesis of weak identification, and the problem is particularly severe for commodities. Pooling our eight asset classes improves identification, and we report pooled results in column (9).

basis shock with FX test assets. We find that carry trade returns are correlated with the basis shock, but in the post-GFC period, carry trade returns are smaller than in the pre-GFC period. This example illustrates the costs and benefits of using the full sample for mean returns. If we believe carry still earns a large risk premium, but happens to have not done as well during the post-GFC period, using the long sample provides a better estimate of the price of risk for the basis shock. If instead we believe that the risk premium of carry has declined, then using only the post-GFC sample is preferable.

[46] Specifically, we use the multi-factor version of the test described in the appendix of Kleibergen and Zhan (2020). We report the F test associated with their statistic to account for the "large N, small T" nature of some of our regressions. We modify their test slightly to account for the fact that when we pool asset classes, we have one intercept for each asset class in the asset-pricing equation as opposed to a single intercept. Unfortunately, the other robust inference methods described by Bryzgalova (2020) and Kleibergen and Zhan (2020) could not be directly applied to our setting.

Our main outcome of interest is the H1 hypothesis that the prices of risk are equal to the mean excess returns of Intermediary Equity and negative of the forward CIP return. We are unable to reject this hypothesis when we pool across asset classes to achieve more precise identification. Our point estimates in the pooled specification ($\lambda_w = 0.472, \lambda_x = -0.0485$) are in fact quite close to the mean excess returns. Note also that our point estimates for the price of the basis risk, λ_x, are strikingly consistent across the asset classes (except for equities, which has large standard error).

The H1 hypothesis is rejected at conventional thresholds in the US bond and FX asset classes due to (respectively) very low and very high estimates for the risk price λ_w. With regards to the FX asset class, three points are worth mentioning. First, the KZ p-value is high, indicating that there may be an insufficient spread in the betas of the interest-rate sorted portfolios to the intermediary asset pricing factors to identify the relevant prices of risk, in which case the standard errors on our estimates might be misleading. Second, some authors (e.g. Burnside et al. (2011)) have argued that the factors that price the carry trade are disconnected from the factors that price other assets; consistent with this, our point estimates can be interpreted as saying that the carry factor is correlated with intermediary equity returns but carries a higher risk price than can be justified by that correlation. Third, as noted in footnote 45, the carry trade has performed less well in recent years; our results that use only the post-GFC sample to estimate mean returns (Internet Appendix Table A28) estimate prices of risk for the FX asset class that are close to our directly-estimated risk prices.

With regards to US bonds, the negative price of risk estimated for λ_w appears only when including the March 2020 COVID crisis. As noted by, for example, He et al. (2021), during this episode longer-dated Treasury bonds initially fell in price, in contrast to the price increases observed during prior crisis episodes. Moreover, these movements were large relative to the usual degree of volatility in Treasury yields during the post-GFC period. As a result, the inclusion of March 2020 in the sample has a large impact on our estimates of the beta between Treasury bonds and our risk factors; of course, it also affects the betas estimated for other, more volatile assets, but to a smaller degree. Internet Appendix Table A14 presents results for a data sample that ends in December 2019. The pooled results are similar to those obtained using the full data sample, but for some asset classes, and in particular for US bonds, the point estimates differ substantially.

We consider a variety of alternative specifications in the Internet Appendix. The finding of a low (negative) intermediary risk price for US bonds and an excessively large intermediary risk price for currencies appear in almost all of these specifications, including specifications that replicate the HKM analysis and do not include our basis factor.

Our model emphasizes that the SDF should include proxies for both intermediary wealth returns and future investment opportunities. For this reason, we view our forward CIP return factor as complement to the HKM intermediary equity return measure. However, as discussed above, we cannot rule out the possibility that our measure is instead a better proxy for intermediary wealth returns. Internet Appendix Tables A15, A16, A17, and A18 all run two-factor models involving the Market and an intermediary-related factor (the HKM factor, the HKM intermediary equity return, the AEM broker-dealer leverage factor, and the "Top-Six First PC" portfolio return, respectively). The price of the HKM factors in the pooled regressions are not significantly different from zero. The AEM leverage factor helps price equity portfolios, but is not priced consistently across asset classes. In contrast, our CIP risk factor is consistently priced across asset classes and yields a significant price of risk in the pooled regressions. More discussion on how CIP risk factor compares with the HKM and AEM factors can be found in Internet Appendix Section I.

The Internet Appendix also presents a number of other variants on Table 8. There is a variant (Table A21) in which we use the HKM capital ratio innovation (along with the Market and forward CIP return), which is non-tradable and is the primary specification in HKM. In this case, we can only test whether the risk prices of the traded factors are consistent with their excess returns, and our results are noisier both in terms of standard errors and with respect to the weak identification test. The Internet Appendix also contains variants that use alternative measures in the place of the "Top-Six First PC" portfolio return. Tables A23 and A24 use, respectively, AUD-JPY and USD-JPY, and Tables A25, A26, and A27 use the other portfolios of forward CIP returns described in Table 3. Table A29 uses the AR(1) innovation of the 3m OIS AUD-JPY spot basis instead of a forward CIP return.[47] Table A30 replaces the forward CIP return in Table 8 with the AR(1) innovation (following HKM) of the first principal component of the near-arbitrages described in Section 4.1, scaled to match the volatility of the AUD-JPY forward CIP return. These variants generate results that are similar to those of Table 8.

5 Conclusion

We provide direct evidence that innovations to the cross-currency bases are correlated with the SDF. These results are consistent with our motivating hypothesis, derived from an intermediary-based asset pricing framework and intertemporal hedging considerations. They

[47] An AR(1) model provides a reasonable description of the spot basis post-GFC– the correlation between the AR(1) innovation and the forward CIP return for AUD-JPY is 0.79 in the post-GFC data. However, the forwards contain information not captured by the spot basis. For example, there was a large, correctly anticipated spike in the 3m spot basis across year end 2019; such spikes were small or non-existent for the 3m tenor in prior years. As a result, the AR(1) innovation and forward CIP returns differ sharply in fall 2019.

are also consistent with the correlation between the basis and other near-arbitrages, the correlation between the basis and measures of intermediary wealth, and with our cross-sectional asset pricing tests. Taken together, we view our results as strongly supportive of intermediary asset pricing theory.

More broadly, we view this paper as beginning an investigation in the dynamics and pricing of arbitrages induced by regulatory constraints. If intermediaries play a central role in both asset pricing and the broader economy, then the question of how to measure the constraints they face and the properties of those constraints is of first-order importance.

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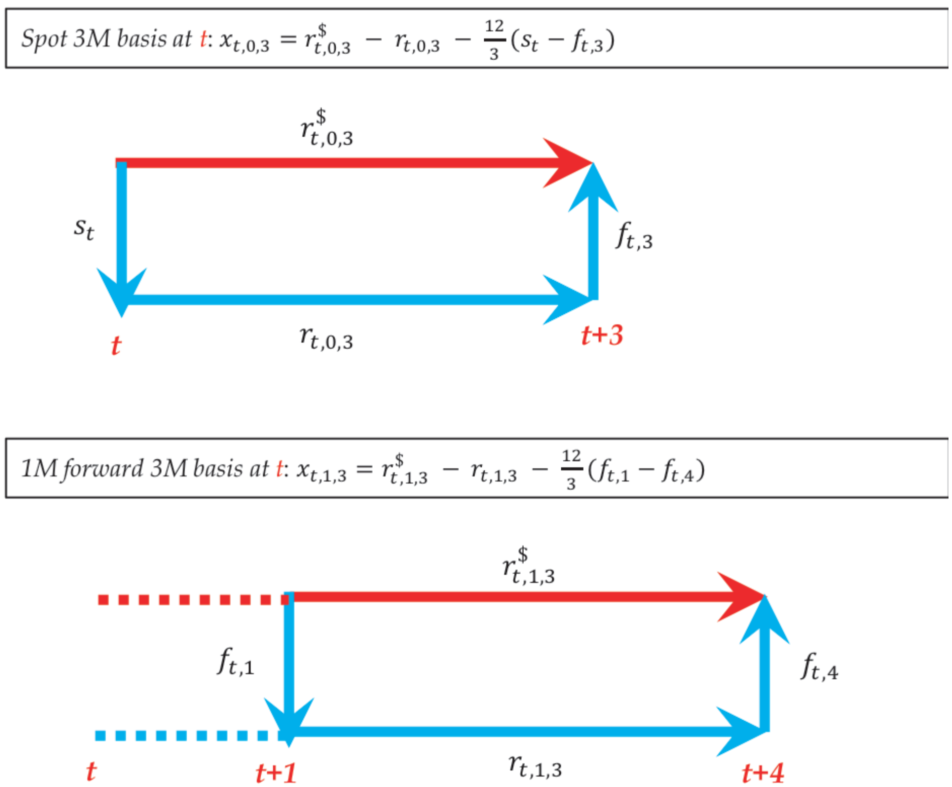
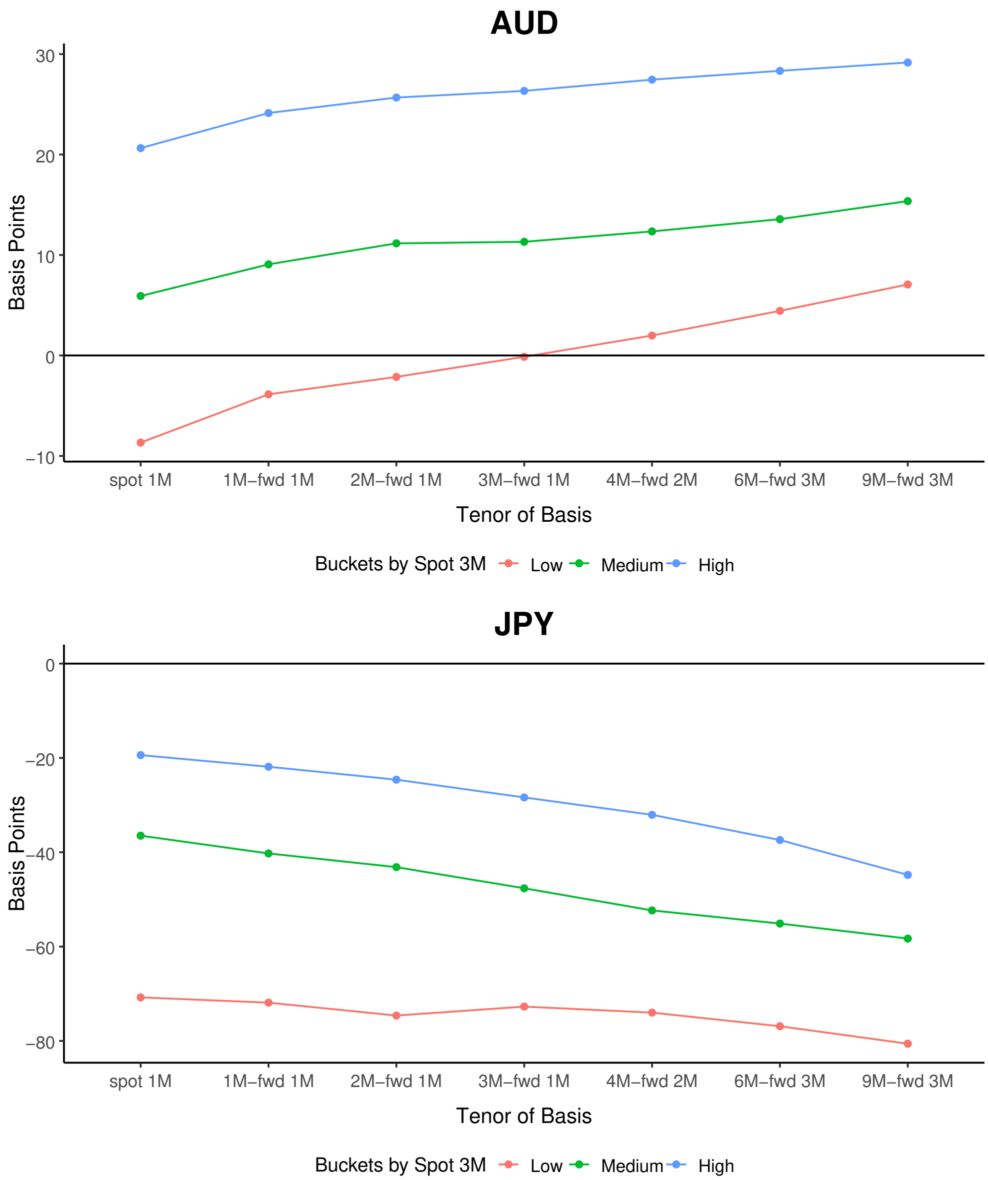
Figures and Tables

Figure 1: **Illustration of spot vs. forward cross-currency basis**



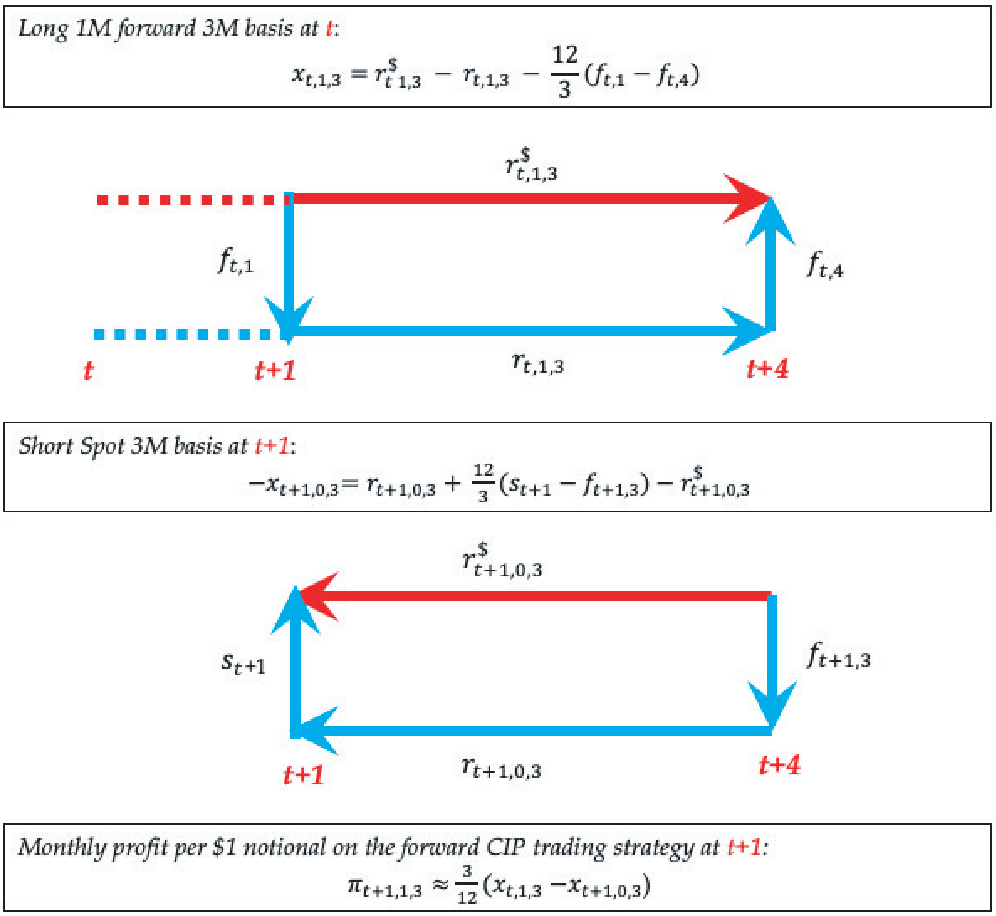
Notes: This figure illustrates the spot 3M cross-currency basis and the 1M-forward 3M cross-currency basis. The spot basis is $x_{t,0,3}$ as defined in the text, and the forward basis is $x_{t,1,3}$ as defined in the text.

Figure 2: **Term Structure of the Forward Cross-Currency Basis**



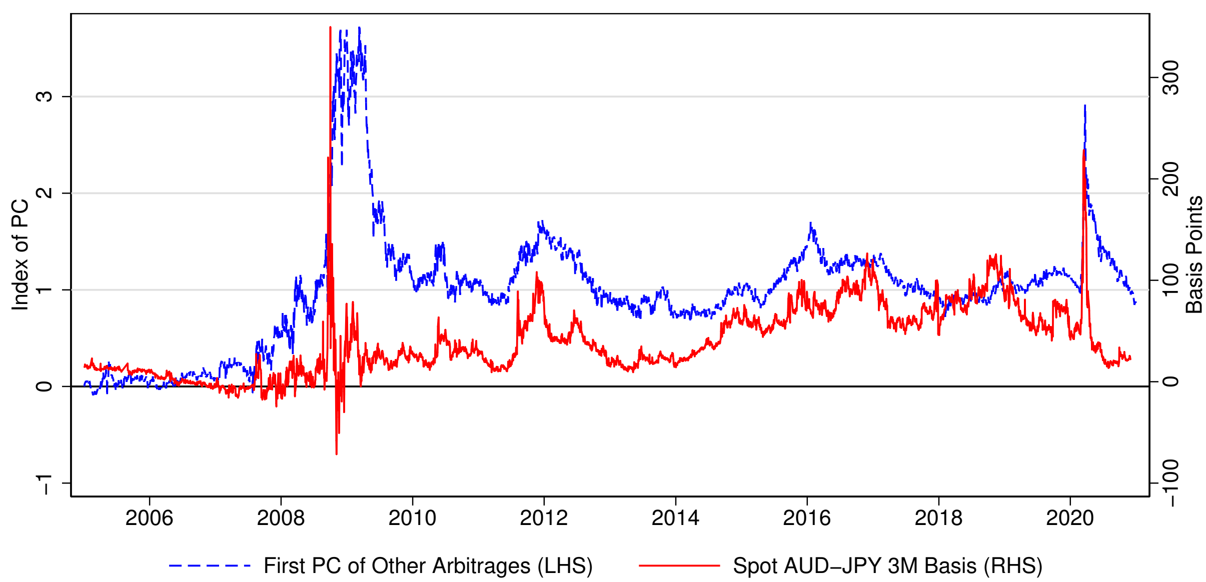
Notes: This figure illustrates the time series average spot and forward-starting cross-currency bases in AUD and JPY, vis-à-vis the USD, respectively, as defined in Equation (8). For each currency, the sample from July 2010 to December 2020 is split into three sub-samples based on the tercile of the level of the spot 3M OIS cross-currency basis. Within each sub-sample, the time series average of the relevant spot/forward OIS cross-currency basis is shown.

Figure 3: **Illustration of the forward CIP trading strategy**



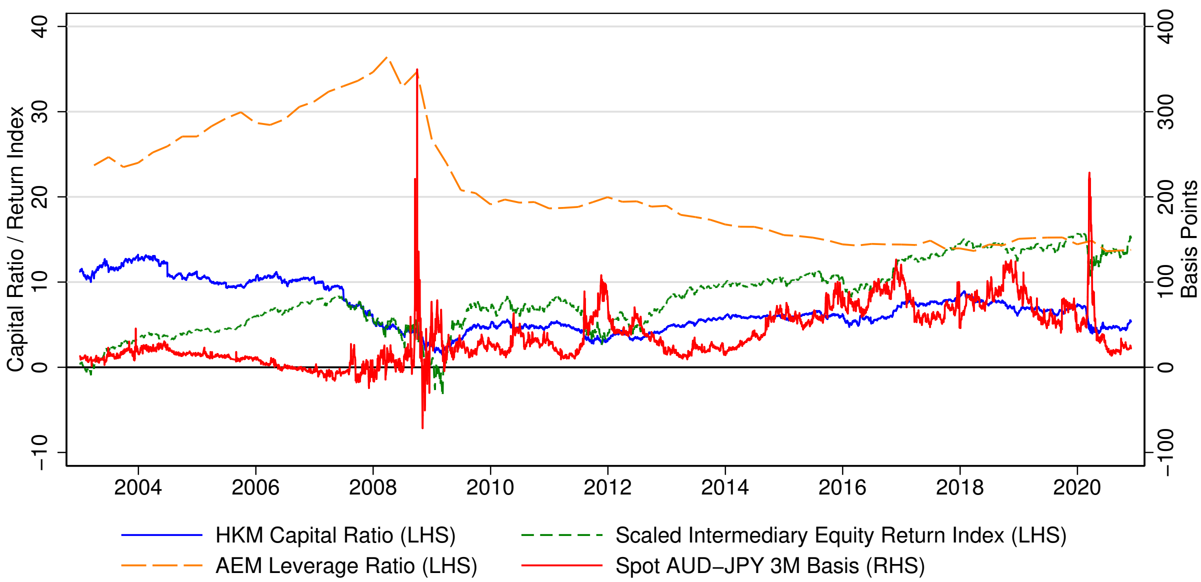
Notes: This figure illustrates the return on a 1M-forward 3M forward CIP trading strategy. At time t, the trader enters the forward basis, $x_{t,1,3}$, which is the forward direct interest less the forward synthetic interest. At time $t+1$, the trader unwinds the spot basis, $-x_{t+1,0,3}$, which is the spot synthetic interest less the spot direct interest. The realized monthly profit per dollar notional on this forward CIP trading strategy is approximately the sum of the two bases: $x_{t,1,3} + (-x_{t+1,0,3})$, normalized by the duration 3/12.

Figure 4: **Cross-Currency Basis and Other Near-Arbitrages**



Notes: This figure plots the daily spot 3M AUD-JPY cross-currency basis and the scaled first principal component of seven other near-arbitrages: the bond-CDS basis, the CDS-CDX basis, the US Libor tenor basis, the 30-year Treasury-swap spread, the Refco-Treasury spread, the KfW-Bund spread, and the TIPS-Treasury spread. The details of these other near-arbitrages are given in Internet Appendix G.

Figure 5: **Cross-Currency Basis and Intermediary Wealth**



Notes: This figure plots the monthly spot 3M AUD-JPY cross-currency basis and measures of intermediary wealth and constraints from 2003 to 2020. The HKM Capital Ratio (in percent) is the equity capitalization ratio of the primary dealer. The cumulative intermediary equity return is based on the value-weighted return of the equity of primary dealers calculated from January 2003 and scaled by 10. The AEM leverage ratio (in percent) is calculated as the ratio of book assets to book equity for the broker-dealer sector from the Flow of Funds.

Table 1: **Forward CIP Trading Profits and Additional Properties for USD-Based Currency Pairs**

Panel A: Summary Statistics of Returns on OIS 1M-fwd 3M Forward CIP Trading Strategy

	Mean			Sharpe Ratio		
	Pre-GFC	GFC	Post-GFC	Pre-GFC	GFC	Post-GFC
AUD_USD	0.98	4.74	7.45***	0.26	0.12	1.24***
	(0.98)	(19.76)	(1.81)	(0.27)	(0.51)	(0.31)
CAD_USD	-0.76	1.79	5.55***	-0.21	0.06	0.90***
	(1.59)	(15.54)	(1.62)	(0.44)	(0.48)	(0.27)
GBP_USD	-1.50**	9.36	4.62***	-0.50*	0.28	0.68***
	(0.73)	(15.67)	(1.72)	(0.26)	(0.41)	(0.22)
EUR_USD	-1.10*	13.68	-1.73	-0.60*	0.33	-0.17
	(0.59)	(19.47)	(2.56)	(0.31)	(0.40)	(0.27)
CHF_USD	-1.37	5.33	-3.59	-0.36	0.13	-0.25
	(0.87)	(17.43)	(4.78)	(0.27)	(0.40)	(0.36)
JPY_USD	-1.88*	8.92	-8.79**	-0.79*	0.18	-0.63*
	(0.97)	(22.98)	(3.57)	(0.41)	(0.44)	(0.35)

Panel B: Post-GFC Properties

	Mean Fwd CIP Trad. Ret.	Average Basis	Average Slope	Avg. Interest Diff. vs. USD	Corr SPX and FX
AUD_USD	7.45	9.43	6.37	1.63	0.56
CAD_USD	5.55	-12.34	5.46	0.33	0.53
GBP_USD	4.62	-15.99	4.65	-0.19	0.36
EUR_USD	-1.73	-34.08	-1.24	-0.67	0.16
CHF_USD	-3.59	-51.84	-3.55	-0.85	-0.03
JPY_USD	-8.79	-44.89	-7.86	-0.62	-0.27

Notes: Panel A of this table reports the annual profits and annualized Sharpe ratios from the OIS 1M-forward 3M forward CIP trading strategy vis-à-vis the USD. Pre-GFC is 2003-01-01 to 2007-06-30, GFC is 2007-07-01 to 2010-06-30, and Post-GFC is 2010-07-01 to 2020-12-31 (CHF ends 2017-12-31). Newey-West standard errors are reported in parentheses, where the bandwidth is chosen by the Newey and West (1994) selection procedure. *, **, and *** denote significance levels at 10%, 5%, and 1% confidence levels. Panel B of this table reports additional characteristics the USD-based currency pairs post-GFC. "Mean Fwd CIP Trad. Ret." is the annualized profit from the forward CIP trading strategy; "Average Basis" is the average spot 3M OIS cross-currency basis; "Average Slope" is the average spread between the 1M-forward 3M and spot 3M OIS cross-currency basis; "Avg. Int. Rate Diff." is the average spread between the 3M foreign OIS rate and the US OIS rate; and "Corr SPX and FX" is the correlation between weekly currency returns of going long the foreign currency and shorting the USD and the weekly returns on the S&P 500 index.

Table 2: **Summary Statistics of Currency Pair Returns on OIS 1M-forward 3M Forward CIP Trading Strategy**

	Mean			Sharpe Ratio			Post-GFC Metrics	
	Pre-GFC	GFC	Post-GFC	Pre-GFC	GFC	Post-GFC	Avg Basis	Int. Rate Diff.
AUD_CHF	2.44**	-0.73	9.85*	0.49*	-0.03	0.65	60.22	2.47
	(1.07)	(10.33)	(5.25)	(0.26)	(0.37)	(0.41)		
AUD_JPY	2.36*	-3.20	16.25***	0.58*	-0.12	1.18***	54.32	2.25
	(1.38)	(9.78)	(3.57)	(0.35)	(0.37)	(0.39)		
USD_CHF	1.37	-5.33	3.59	0.36	-0.13	0.25	51.84	0.85
	(0.87)	(17.43)	(4.78)	(0.27)	(0.40)	(0.36)		
USD_JPY	1.88*	-8.92	8.79**	0.79*	-0.18	0.63*	44.89	0.62
	(0.97)	(22.98)	(3.57)	(0.41)	(0.44)	(0.35)		
CAD_CHF	1.09	-4.80	9.02**	0.21	-0.17	0.66	44.22	1.18
	(1.85)	(8.17)	(4.48)	(0.40)	(0.28)	(0.41)		
AUD_EUR	2.12**	-8.91	9.18***	0.58**	-0.39	0.89***	43.51	2.30
	(0.88)	(8.30)	(2.76)	(0.25)	(0.34)	(0.30)		
GBP_CHF	0.20	3.77	8.02*	0.04	0.17	0.60	38.48	0.66
	(0.94)	(6.92)	(4.35)	(0.21)	(0.32)	(0.40)		
USD_EUR	1.10*	-13.68	1.73	0.60*	-0.33	0.17	34.08	0.67
	(0.59)	(19.47)	(2.56)	(0.31)	(0.40)	(0.27)		
CAD_JPY	0.04	-7.19	14.26***	0.01	-0.24	1.20***	32.55	0.96
	(1.40)	(11.13)	(2.86)	(0.36)	(0.36)	(0.40)		
GBP_JPY	0.02	1.41	13.40***	0.00	0.06	1.32***	28.91	0.43
	(0.88)	(9.78)	(2.66)	(0.27)	(0.41)	(0.39)		

Standard errors in parentheses

Notes: This table reports the annual profits and annualized Sharpe ratios from the OIS 1M-forward 3M forward CIP trading strategy for the ten currency pairs with the largest average Post-GFC spot 3M bases. Pre-GFC is 2003-01-01 to 2007-06-30, GFC is 2007-07-01 to 2010-06-30, and Post-GFC is 2010-07-01 to 2020-12-31 (CHF ends 2017-12-31). "Avg. Basis" is the average spot 3M OIS cross-currency basis post-GFC, and "Int. Rate Diff." is the average spread between the 3M foreign OIS rate and the US OIS rate post-GFC. Newey-West standard errors are reported in parentheses, where the bandwidth is chosen by the Newey and West (1994) selection procedure. *, **, and *** denote significance levels at 10%, 5%, and 1% confidence levels.

Table 3: **Summary Statistics of Portfolio Returns on OIS 1M-forward 3M Forward CIP Trading Strategy**

	Mean			Sharpe Ratio		
	Pre-GFC	GFC	Post-GFC	Pre-GFC	GFC	Post-GFC
Classic Carry (AUD-JPY)	2.36*	-3.20	16.25***	0.58*	-0.12	1.18***
	(1.38)	(9.78)	(3.57)	(0.35)	(0.37)	(0.39)
Dollar-Neutral Carry	0.16	-5.84	11.16***	0.07	-0.30	1.27***
	(0.83)	(7.56)	(2.29)	(0.37)	(0.36)	(0.40)
Dynamic Top-Five Basis	0.73	-5.95	11.27***	0.32	-0.20	1.03***
	(0.84)	(12.45)	(2.80)	(0.37)	(0.38)	(0.39)
Static Top-Six Basis	0.77	-6.63	10.65***	0.36	-0.24	1.00**
	(0.78)	(11.46)	(2.74)	(0.36)	(0.38)	(0.39)
Simple Dollar	-0.82	7.47	1.41	-0.44	0.20	0.20
	(1.15)	(18.15)	(1.88)	(0.60)	(0.46)	(0.25)
Top-Six First PC	1.06	-8.00	13.87***	0.38	-0.23	1.00**
	(1.04)	(14.83)	(3.55)	(0.37)	(0.39)	(0.39)

Standard errors in parentheses

Notes: This table reports the annual profits and annualized Sharpe ratios from the OIS 1M-forward 3M forward CIP trading strategy. All statistics are reported by period: Pre-GFC is 2003-01-01 to 2007-06-30, GFC is 2007-07-01 to 2010-06-30, and Post-GFC is 2010-07-01 to 2020-12-31. The "Classic Carry" portfolio is the forward CIP trading strategy for the AUD-JPY pair. The "Dollar-Neutral Carry" portfolio longs the forward CIP trading strategy in AUD, CAD, and GBP and shorts the forward CIP trading strategy in JPY and EUR. The "Dynamic Top-Five Basis" portfolio has equal weight in the 5 currency pairs that exhibit the highest spot 3M basis, rebalanced monthly. The "Static Top Six Basis" portfolio has equal weights in the six non-CHF currency pairs with the largest average spot 3M basis post-GFC shown in Table 2. The "Simple Dollar" portfolio puts equal weights on the forward CIP trading strategy for all non-CHF sample currencies vis-à-vis the USD. The "Top-Six First PC" portfolio is the first principal component of the six non-CHF currency pair returns with the largest average spot 3M basis post-GFC shown in Table 2. Newey-West standard errors are reported in parentheses, where the bandwidth is chosen by the Newey and West (1994) selection procedure. *, **, and *** denote significance levels at 10%, 5%, and 1% confidence levels.

Table 4: **Pre/Post COVID Statistics of Portfolio Returns on OIS 1M-forward 3M Forward CIP Trading Strategy**

	Mean			Sharpe Ratio		
	Pre 2020	Post 2020	Overall	Pre 2020	Post 2020	Overall
Classic Carry (AUD-JPY)	15.82***	20.72	16.25***	1.58***	0.62	1.18***
	(3.01)	(25.80)	(3.57)	(0.33)	(0.89)	(0.39)
Dollar-Neutral Carry	11.15***	11.29	11.16***	1.72***	0.54	1.27***
	(2.04)	(15.14)	(2.29)	(0.37)	(0.81)	(0.40)
Dynamic Top-Five Basis	11.33***	10.68	11.27***	1.51***	0.38	1.03***
	(2.32)	(20.81)	(2.80)	(0.34)	(0.82)	(0.39)
Static Top-Six Basis	10.76***	9.54	10.65***	1.48***	0.35	1.00**
	(2.27)	(20.43)	(2.74)	(0.33)	(0.82)	(0.39)
Simple Dollar	0.87	6.99	1.41	0.19	0.38	0.20
	(1.49)	(14.57)	(1.88)	(0.32)	(0.71)	(0.25)
Top-Six First PC	14.02***	12.31	13.87***	1.50***	0.35	1.00**
	(2.92)	(26.77)	(3.55)	(0.33)	(0.83)	(0.39)

Standard errors in parentheses

Notes: This table reports the annual profits and annualized Sharpe ratios from the OIS 1M-forward 3M forward CIP trading strategy by sub-samples. All statistics are reported by period: Pre-2020 is 2003-01-01 to 2019-12-31, Post-2020 is 2020-1-1 to 2020-12-31, and the overall is the full sample period. The "Classic Carry" portfolio is the forward CIP trading strategy for the AUD-JPY pair. The "Dollar-Neutral Carry" portfolio longs the forward CIP trading strategy in AUD, CAD, and GBP and shorts the forward CIP trading strategy in JPY and EUR. The "Dynamic Top-Five Basis" portfolio has equal weight in the 5 currency pairs that exhibit the highest spot 3M basis, rebalanced monthly. The "Static Top Six Basis" portfolio has equal weights in the six non-CHF currency pairs with the largest average spot 3M basis post-GFC shown in Table 2. The "Simple Dollar" portfolio puts equal weights on the forward CIP trading strategy for all non-CHF sample currencies vis-à-vis the USD. The "Top-Six First PC" portfolio is the first principal component of the six non-CHF currency pair returns with the largest average spot 3M basis post-GFC shown in Table 2. Newey-West standard errors are reported in parentheses, where the bandwidth is chosen by the Newey and West (1994) selection procedure. *, **, and *** denote significance levels at 10%, 5%, and 1% confidence levels.

Table 5: **Returns on ON-TN Forward CIP Trade and Quarter-Ends**

	(1) ON basis	(2) Lagged TN basis	(3) ON-TN Forward Profit
QE Dummy	154.1***	207.4***	53.25**
	(32.77)	(34.83)	(25.17)
Constant	10.98***	15.17***	4.194***
	(0.580)	(0.545)	(0.537)
Observations	4,953	4,953	4,953
R-squared	0.112	0.186	0.020

Notes: This table reports regression results for the overnight CIP deviations (Column 1), one-day lagged tomorrow/next CIP deviations (Column 2) and the return on the ON-TN forward CIP trade (Column 3), or the difference between Column 2 and Column 3. The independent variable is a quarter-end (QE) dummy, which is equal to one if the date is equal to the last business date of the quarter. The sample currencies include CHF, EUR and JPY. The CIP deviations are calculated as the difference between swapped foreign central bank deposit rate into U.S. dollars and the U.S. interest rate on excess reserves. The sample period is post-GFC from 2010-07-01 to 2020-12-31. Robust standard errors are reported in the parentheses. Details on the ON and TN CIP deviations can be found in Internet Appendix F.

Table 6: Pricing Fwd CIP Returns with Intermediary Wealth

	1M-fwd 3M classic pc forward CIP returns						
	Monthly Returns					Quarterly Returns	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Market		0.011*		0.009	0.006		0.020***
		(0.006)		(0.009)	(0.008)		(0.006)
Int. Equity			0.007**	0.002			
			(0.003)	(0.004)			
HKM Factor					0.004		
					(0.003)		
AEM Factor							0.0001
							(0.0001)
Constant	0.050***	0.036***	0.045***	0.037***	0.041***	0.150***	0.079**
	(0.010)	(0.010)	(0.009)	(0.011)	(0.011)	(0.032)	(0.034)
Observations	126	126	126	126	126	42	42

Notes: In this table, we regress the returns of the "Top-Six First PC" forward CIP trading portfolio on a constant and the intermediary wealth and constraint proxies described in the text: Market, Intermediary Equity, the HKM Factor, and the AEM factor. Regressions (1) through (4) use monthly returns. Regressions (5) and (6) use quarterly returns. Standard errors are computed using the Newey-West kernel with a twelve-month (monthly) or four-quarter (quarterly) bandwidth. *, **, and *** denote significance levels at 10%, 5%, and 1% confidence levels.

Table 7: Bayesian Posterior Prob of SDF Models with Fwd. Ret. PC

Factor Space	Model	Probability	Subtotal
{Market, Int. Equity,	Market	0.074	
Fwd. Ret. PC}	Int. Equity	0.002	
	Market + Int. Equity	0.046	0.123
	Fwd. Ret. PC	0.380	
	Market + Fwd. Ret. PC	0.262	
	Int.Equity + Fwd. Ret. PC	0.048	
	Market + Int. Equity + Fwd. Ret. PC	0.187	0.877
{HKM Factor, Market,	HKM Factor	0.001	
Fwd. Ret. PC}	HKM Factor + Market	0.111	0.112
	HKM Factor + Fwd. Ret. PC	0.037	
	HKM Factor + Market + Fwd. Ret. PC	0.851	0.888
{AEM Factor, Market,	AEM Factor	0.228	
Fwd. Ret. PC}	AEM Factor + Market	0.212	0.440
	AEM Factor + Fwd. Ret. PC	0.449	
	AEM Factor + Market + Fwd. Ret. PC	0.112	0.560

Notes: In this table, we report posterior probabilities for factor models that do and do not include the forward CIP return on the "Top-Six First PC" portfolio, using the method of Chib et al. (2020) (see Internet Appendix J for details).

Table 8: **Cross-sectional Asset Pricing Tests, 2-Factor.**

	(1) US	(2) Sov	(3) FX	(4) Opt	(5) FwdArb	(6) CDS	(7) FF6	(8) Comm	(9) 1-8
Int. Equity	-0.309	0.757	2.692	0.612	-1.476	1.217	0.984	0.465	0.478
	(0.409)	(1.060)	(0.795)	(0.767)	(8.123)	(1.068)	(0.613)	(1.195)	(0.550)
Fwd. CIP Ret. PC1	-0.0595	-0.0322	-0.0586	-0.0751	-0.0405	-0.101	0.0299	-0.146	-0.0485
	(0.0353)	(0.0721)	(0.0416)	(0.0396)	(0.0310)	(0.0730)	(0.152)	(0.110)	(0.0199)
Intercepts	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MAPE (%/mo.)	0.047	0.047	0.052	0.058	0.014	0.006	0.097	0.043	
H1 p-value	0.051	0.970	0.016	0.825	0.943	0.302	0.306	0.639	0.966
KZ p-value	0.000	0.545	0.217	0.016	0.001	0.069	0.077	0.864	0.000
N (assets)	11	6	11	12	13	5	6	6	70
N (beta, mos.)	126	126	126	126	126	126	126	126	
N (mean, mos.)	388	312	446	300	126	198	1133	359	

Standard errors in parentheses

Notes: This table reports estimates for the price of risk (λ in Equation (12)) from the various asset classes described in Internet Appendix Section K. “Fwd. CIP Ret. PC1” is the negative of the return on the “Top-Six First PC” forward CIP trading portfolio as described in the text and “Int. Equity” is the intermediary equity return of He et al. (2017). Intercepts indicates an intercept is used for each asset class (one intercept per column, with six in (9), which pools the eight asset classes). MAPE is mean absolute pricing error of monthly returns. H1 p-value tests whether the price of the Fwd. CIP Ret. PC1 and Int. Equity risks are equal to the mean excess returns of those trading strategies. KZ p-value is the p-value of the Kleibergen and Zhan (2020) test rejecting reduced rank for the betas of the test assets. Standard errors are computed using GMM with the Newey-West kernel and a twelve-month bandwidth. Units are in percentage points.

Internet Appendix (not for publication)
"Are Intermediary Constraints Priced?"

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B Model Details

In this Internet Appendix section we present a more detailed description of the model outlined in Section 1, and a more formal statement of the key results.

Our model adopts the approach of He and Krishnamurthy (2011) and the subsequent intermediary asset pricing literature (surveyed in He et al. (2017)), and in particular the idea that the manager of the intermediary is an agent who should price assets. The model is a discrete time version of He and Krishnamurthy (2011). We add to He and Krishnamurthy (2011) a variety of assets, including both "cash" assets and derivatives, and a regulatory constraint. We study a manager with CRRA or Epstein-Zin preferences (rather than focus on log preferences), because these preferences will allow us to discuss the role that intertemporal hedging concerns play in the model.[48]

[48] In augmenting the He and Krishnamurthy (2011) model with Epstein-Zin preferences, we are building on Di Tella (2017) among others.

The model is based on He and Krishnamurthy (2011), but is partial equilibrium in that it considers only that intermediary manager's problem and not market clearing conditions. In this sense, the model follows the spirit of the standard consumption-based asset pricing approach. Our maintained assumption is that asset prices are consistent with the manager's Euler equations. This assumption has a particularly significant implication in the presence of arbitrage opportunities: it implies that arbitrage can exist if and only if constraints prevent the intermediary from taking advantage of the arbitrage.[49]

The manager is endowed with the ability to run an intermediary that survives for a single period. In the beginning of the period, the manager will raise funds from households in the form of both debt and equity, subject to various constraints, and choose how much of her own wealth to contribute. The manager then invests these funds in a variety of assets. At the end of the period, returns realize and the intermediary is dissolved. The manager receives a payout based on her equity share in the intermediary. This payout, plus any savings the manager holds outside the intermediary, determine the manager's wealth entering into the next period.

Let W_t^M denote the manager's wealth at the beginning of period t, and let z_t be a state variable that determines the conditional (on time t information) distribution of asset returns. These two variables are the state variables of the manager's optimization problem and are the relevant portions of the manager's information set. Expectations should be understood as conditioning on these two variables,

$$E_t[\cdot] = E[\cdot|W_t^M, z_t].$$

At the beginning of the period, the manager must decide on a contractual structure for

[49]We would like to thank Andreas Stathopoulos for a very helpful discussion on this point.

the intermediary she runs. The intermediary begins by raising equity capital $N_t \geq 0$. Of the initial equity capital, N_t^M is contributed by the manager, with the remainder coming from households. The manager receives a share ϕ_t of the wealth that will be liquidated when the intermediary is dissolved at the end of the period, with the remainder going to households. Note that the share ϕ_t is not necessarily equal to the proportion of the equity that the manager contributes; define the fee

$$f_t^m \equiv \frac{\phi_t N_t}{N_t^M}$$

as the ratio of what the manager receives to what she contributes.

The manager raises equity and debt from households in a competitive market. Let M_{t+1}^H be the household's SDF, and let $\hat{N}_{t+1}$ be the value of the intermediary's equity after returns are realized and the debt is repaid (we define this variable in more detail below). Let B_t be the face value of the intermediary's debt, and let $R_t^b = \exp(r_t^b)$ be its interest rate. For any capital structure $(\phi_t, N_t^M, N_t, B_t, R_t^b)$ proposed by a manager with wealth W_t^M in state z_t, households will be willing to purchase the equity if

$$N_t - N_t^M \leq (1 - \phi_t) E[M_{t+1}^H \hat{N}_{t+1} | z_t, W_t^M, (\phi_t, N_t^M, N_t, B_t, R_t^b)].$$

The intermediary's debt must also be priced by the household's SDF,

$$1 = E_t[M_{t+1}^H R_t^b].$$

Note that the expectation relevant for the equity purchase decision is conditional on the state variables z_t, W_t^M and the capital structure of the intermediary, but not on the intermediary's asset allocation (which we define below). That is, the household must form a conjecture about how the manager will choose to invest, and price the equity accordingly; the manager cannot commit. This is a key friction, which is also employed by He and Krishnamurthy (2011).

We have assumed that the intermediary is risk-free. We are ignoring the possibility of default; the model of He and Krishnamurthy (2011) that we are building on is developed in continuous time with continuous price processes, and hence also excludes the possibility of default. We develop a discrete time model to make the intuition behind our hypothesized SDFs clear, and have found that incorporating the possibility of default obfuscates that intuition.[50]

We next turn to the intermediary's budget constraints. We allow the manager of the intermediary to divert resources from the intermediary instead of investing them. Let $\Delta_t \geq 0$ be the resources diverted. In equilibrium, households will ensure that diversion does not occur by ensuring that ϕ_t, the manager's claim on the assets, is sufficiently high.

Let I be the set of all assets available to the intermediary. We partition this set into "cash" and "derivative" assets, I^c and I^d, assuming that the former require an upfront cash investment whereas the latter are contracts entered into with zero initial net-present-value. Cash assets affect the intermediary's initial budget constraint, whereas the derivatives do not. Let α_t^i be the dollar amount (cash) or notional (derivative) invested in asset i, scaled by the initial non-diverted intermediary equity N_t.

[50]Note, however, that incorporating the possibility of default is necessary for the model to speak to issues like whether it is to preferable to examine OIS or IBOR bases.

The intermediary's initial budget constraint is

$$N_t + B_t = \Delta_t + N_t \sum_{i \in I^c} \alpha_t^i.$$

The excess return (cash assets) or profit per unit notional (derivative assets) of asset i is defined as $R_{t+1}^i - R_t^b$. The distribution of these returns is a function of z_t, and the returns are realized at the end of the period. The intermediary's net worth when it is liquidated at the end of the period is therefore

$$\hat{N}_{t+1} = -R_t^b B_t + N_t \sum_{i \in I^c} \alpha_t^i R_{t+1}^i + N_t \sum_{i \in I^d} \alpha_t^i (R_{t+1}^i - R_t^b),$$

which can be re-written as

$$\hat{N}_{t+1} = R_t^b (N_t - \Delta_t) + N_t \sum_{i \in I} \alpha_t^i (R_{t+1}^i - R_t^b).$$

Using this definition, we can rewrite the household's equity participation constraint as

$$\begin{aligned} N_t - N_t^M \leq & (1 - \phi_t)(N_t - \Delta_t^*) \\ & + N_t (1 - \phi_t) E_t [M_{t+1}^H \sum_{i \in I} \alpha_t^{i*} (R_{t+1}^i - R_t^b)]), \end{aligned}$$

where Δ_t^* and α_t^{i*} are the policies that the household conjectures based on observing the state variables and capital structure.

Lastly, as described in the text, we assume that the intermediary operates under a regulatory constraint that affects only cash assets:

$$1 \geq \sum_{i \in I^c} k^i |\alpha_t^i|.$$

Note that we have assumed that the regulatory constraint cannot limit the cashflow diversion of the manager.[51]

These constraints describe the operation of the intermediary. We next turn to the decisions and preferences of the manager. We assume the manager has Epstein-Zin preferences (Epstein and Zin (1989)), with risk-aversion parameter γ, intertemporal elasticity of substitution parameter ψ, and a subjective discount factor of β, and define $\theta = \frac{1-\gamma}{1-\psi^{-1}}$. Whatever wealth she does not consume or invest in the intermediary, plus any resources she diverts from the intermediary, is saved in risk-free assets, but the manager cannot borrow. When the manager diverts Δ_t resources from the intermediary, she receives only $(1+\chi)^{-1}\Delta_t$, which she can save in the risk-free asset. As a result, her wealth entering the next period is

$$W_{t+1}^M = R_t^b (W_t^M - C_t^M - N_t^M + \frac{\Delta_t}{1+\chi}) + \phi_t \hat{N}_{t+1},$$

where the first term represents the intermediary's outside savings and the second her share of the intermediary's liquidation value.

We now define the Bellman equation describing the manager's problem. The manager

[51] Our model inherits from He and Krishnamurthy (2017) the somewhat awkward assumption that the manager cannot commit when choosing an asset allocation, even though the regulator can limit the manager's asset allocation.

solves

$$V(W_t^M, z_t) = \max_{C_t^M \geq 0, N_t^M \geq 0, N_t \geq 0, \phi_t \in [0,1], \Delta_t \geq 0, \{\alpha_t^i\}_{i \in I}} \{(C_t^M)^{1-\psi^{-1}} + \beta E_t[V(W_{t+1}^M, z_{t+1})^{1-\gamma}]^{\theta^{-1}}\}^{\frac{1}{1-\psi^{-1}}},$$

subject to

$$\begin{aligned}
\hat{N}_{t+1} &= R_t^b(N_t - \Delta_t) + N_t \sum_{i \in I} \alpha_t^i (R_{t+1}^i - R_t^b), \\
W_{t+1}^M &= R_t^b(W_t^M - C_t^M - N_t^M + \frac{\Delta_t}{1+\psi}) + \phi_t \hat{N}_{t+1}, \\
C_t^M + N_t^M &\leq W_t^M, \\
N_t - N_t^M &\leq (1 - \phi_t)(N_t - \Delta_t^*) \\
&\quad + N_t(1 - \phi_t) E_t[M_{t+1}^H \sum_{i \in I} \alpha_t^{i*} (R_{t+1}^i - R_t^b)], \\
\sum_{i \in I^c} k^i |\alpha_t^i| &\leq 1, \\
N_t^M &\leq N_t.
\end{aligned}$$

In defining this problem, we have eliminated the debt level B_t as a choice variable by substituting out the initial budget constraint, and we have assumed that the manager will choose to offer a capital structure acceptable to households. This assumption is without loss of generality, as the manager can always set $N_t^M = N_t$, $\phi_t = 1$, which is equivalent to having her offer rejected. Note also that this problem is part of an equilibrium of a capital raising game. That is, the households expectations Δ_t^* and α_t^{i*} are functions of the proposed capital structure and must be consistent with the manager's ultimate choices given that capital structure.[52]

We next describe a lemma that collects a number of simplifying results, in particular focusing on an equilibrium in which no cashflow diversion occurs in equilibrium and the anticipated asset allocation depends only in the investment opportunities. These results are essentially identical to statements contained in He and Krishnamurthy (2011).

Lemma 1. *In the manager's problem, there exists an equilibrium in which:*

1. *The optimal allocation α_t^{i*} is a function only of the state vector z_t, and satisfies*

$$-1 < E_t[M_{t+1}^H \sum_{i \in I} \alpha_t^{i*}(R_{t+1}^i - R_t^b)] < \frac{1}{\chi},$$

2. *There is no diversion, $\Delta_t = \Delta_t^* = 0$, and the manager's share satisfies $\phi_t^* \geq (1+\chi)^{-1}$,*

3. *The household equity participation constraint binds,*

4. *The manager invests all savings in the intermediary, $C_t^M + N_t^M = W_t^M$, with $N_t^M > 0$,*

5. *The manager's share ϕ_t^* and fee f_t^M are functions only of z_t, with*

$$f_t^M(z_t) = \frac{\phi_t^*(z_t)}{\phi_t^*(z_t) - (1 - \phi_t^*(z_t))E_t[M_{t+1}^H \sum_{i \in I} \alpha_t^{i*}(R_{t+1}^i - R_t^b)]}.$$

6. *$f_t^M(z_t) \geq 1$, strictly if and only if $E_t[M_{t+1}^H \sum_{i \in I} \alpha_t^{i*}(R_{t+1}^i - R_t^b)] > 0$, and $\phi_t^* = (1+\chi)^{-1}$ if $f_t^M > 1$.*

Proof. See below. □

[52] Formally, we do not require that this equilibrium be subgame perfect. This simplification allows us to focus directly on an equilibrium in which the manager puts all her savings in the intermediary. He and Krishnamurthy (2011) Lemma 2 proves (in the context of their model; our model is essentially the discrete time version) that this outcome holds in all equilibria.

With these results, the manager's final wealth is

$$\begin{aligned}W_{t+1}^{M} &= \phi_t \hat{N}_{t+1} \\ &= (W_t^M - C_t^M) f_t^M(z_t)(R_t^b + \sum_{i \in I} \alpha_t^i (R_{t+1}^i - R_t^b)),\end{aligned}$$

and the manager's problem can be written as

$$\begin{aligned}V(W_t^M, z_t) = &\max_{C_t^M \geq 0, \{\alpha_t^i\}_{i \in I}} \\ &\{(C_t^M)^{1-\psi^{-1}} + \beta E_t[V(W_{t+1}^M, z_{t+1})^{1-\gamma}]^{\theta^{-1}}\}^{\frac{1}{1-\psi^{-1}}},\end{aligned}$$

subject to

$$W_{t+1}^M = (W_t^M - C_t^M) f_t^M(z_t)(R_t^b + \sum_{i \in I} \alpha_t^i (R_{t+1}^i - R_t^b)),$$

$$\sum_{i \in I^c} k^i |\alpha_t^i| \leq 1.$$

It is useful to define the log return on the manager's wealth,

$$\begin{aligned}r_{t+1}^w &= \ln(f_t^M) + \ln(R_t^b + \sum_{i \in I} \alpha_t^i (R_{t+1}^i - R_t^b)) \\ &= \ln(\frac{W_{t+1}^M}{W_t^M - C_t^M}).\end{aligned}$$

This definition includes the fee f_t^M, unlike the usual definition of the return on wealth. As shown in Lemma 1, this fee will be positive if and only the intermediary's portfolio earns an abnormal return under the household's SDF, and in this case the "inside equity" constraint $\phi_t^* \geq (1+\chi)^{-1}$ will bind. This is natural, but not guaranteed, in the presence of arbitrage opportunities.

For example, if the intermediary can only 1) engage in arbitrage or 2) buy assets that are also priced under the household's SDF, and arbitrage opportunities exist, then it must the case that $f_t^M > 1$. However, if the intermediary can also buy assets that are "expensive" from the household's perspective, then even in the presence of arbitrage opportunities it is not necessarily the case that $f_t^M > 1$. This kind of indifference occurs in He and Krishnamurthy (2011) when the inside equity constraint does not bind (normal times).

In the main text, we assume that $f_t^M = 1$ to illustrate the point that the regulatory constraint can bind even if the inside equity constraint does not. In the remainder of this Internet Appendix, we present results that include f_t^M. Note also that f_t^M can vary over time (in particular, when the economy transitions from "normal" to "crisis" times), and that the increase in f_t^M in crisis times generates an additional intertemporal hedging motive.[53]

We next derive the Euler equation for consumption and the first-order conditions for portfolio choice in the usual way, following Epstein and Zin (1989). The only complications that our model introduces relative to Epstein and Zin (1989) are the fee f_t^M, which alters the definition of the wealth return, and the constraint, which introduces a multiplier into the portfolio choice problem but does not change the consumption Euler equation. We summarize these equations in the lemma below, and for completeness provide a derivation at the end of this section.

Lemma 2. *Define* $\Delta c_{t+1}^M = \ln(C_{t+1}^M) - \ln(C_t^M)$*, and* $m_{t+1} = \theta \ln(\beta) + (\theta - 1) r_{t+1}^w - \frac{\theta}{\psi} \Delta c_{t+1}^M$*. For the manager's problem, the first-order condition associated with the consumption-savings*

[53]Exploring the interactions between intertemporal hedging and the non-linearity in intermediary asset pricing models is an interesting avenue for future research. We thank David Chapman for pointing out this possibility.

decision is

$$1 = E_t[\exp(m_{t+1} + r^w_{t+1})]$$

and the first-order condition for α^i_t is

$$E_t[\exp(m_{t+1})(R^i_{t+1} - R^b_t)] = \lambda^{RC}_t k^i sgn(\alpha^i_t),$$

Proof. See below. □

Consider in particular the first-order conditions associated with a foreign currency risk-free bond and with a forward contract on the exchange rate. The return on the foreign currency bond is $R^c_t \frac{S_t}{S_{t+1}}$, and the profit of the forward (a derivative) is $\frac{S_{t+1}-F_{t,1}}{S_{t+1}}$ per dollar notional. The two first-order conditions are

$$E_t[\exp(m_{t+1})(R^c_t \frac{S_t}{S_{t+1}} - R^b_t)] = \lambda^{RC}_t k^c sgn(\alpha^c_t)$$

and

$$E_t[\exp(m_{t+1})(\frac{S_{t+1} - F_{t,1}}{S_{t+1}})] = 0.$$

Combining these two equations yields

$$E_t[\exp(m_{t+1})(R^c_t \frac{S_t}{F_{t,1}} - R^b_t)] = \lambda^{RC}_t k^c sgn(\alpha^c_t),$$

or

$$E_t[\exp(m_{t+1})] R^b_t(\exp(-x_{t,1}) - 1) = \lambda^{RC}_t k^c sgn(\alpha^c_t),$$

where $x_{t,1}$ is defined as in the main text. Taking absolute values gives Equation (4).

Combining this equation with the first-order condition for an arbitrary asset i, we have

$$E_t[\exp(m_{t+1})(R^i_{t+1} - R^b_t(1 + sgn(\alpha^i_t)\frac{k^i}{k^c}|1 - \exp -x_{t,1}|)] = 0.$$

We conclude that, holding risk premia constant, the absolute value of the cross-currency basis should predict asset returns, at least for those assets the intermediary is consistently long or short. However, the "holding risk premia" constant caveat is potentially quite important. It may very well be the case that the cross-currency basis co-moves with other variables in z_t that predict changing variances and co-variances, and hence risk premia and expected returns.

We should also emphasize that this prediction is difficult to test. Return predictability regressions often require long time series, but our theory only applies to the period in which regulatory constraints create CIP violations (essentially the post-financial-crisis period). It may be possible to construct stronger tests even in short data samples by imposing structure on the coefficients k^i/k^c, by taking a stand on the nature of the regulatory constraint. For example, a pure leverage constraint might set all of these coefficients to unity for all assets i. Our approach focuses on a different prediction of the model, which we derive next.

Let us consider the first-order condition associated with the wealth portfolio. We have

$$E_t[\exp(m_{t+1})(\sum_{i \in I} \alpha^{i*}_t (R^i_{t+1} - R^b_t))] = \lambda^{RC}_t \sum_{i \in I} \alpha^{i*}_t k^i sgn(\alpha^i_t),$$

which is

$$E_t[\exp(m_{t+1})(\exp(r^w_{t+1} - \ln(f^M_t)) - R^b_t)] = \lambda^{RC}_t.$$

This simplifies to Equation (5) in the $f_t^M = 1$ case.

We next apply the log-normality approximation used by Campbell (1993), and assume that all conditional variances and covariances are constant (i.e. that the model is homoskedastic). Under these assumptions, and using the first-order approximation

$$\ln(1 + \frac{k^i}{k^c} sgn(\alpha_t^i)|1 - \exp(-x_{t,1})|) \approx \frac{k^i}{k^c} sgn(\alpha_t^i)|x_{t,1}|,$$

we can simplify the Euler equation for asset i to

$$E_t[r_{t+1}^i] - r_t^b + \frac{1}{2}(\sigma^i)^2 = \frac{\theta}{\psi}\sigma^{ic} + (1-\theta)\sigma^{iw} + \frac{k^i}{k^c} sgn(\alpha_t^i)|x_{t,1}|, \tag{A1}$$

where $r_{t+1}^i = \ln(R_{t+1}^i)$, $(\sigma^i)^2$ is the conditional variance of the log return, σ^{ic} is the conditional covariance of the log return and log consumption growth, and σ^{iw} is the conditional covariance of the log return and the log wealth return. Compared to the textbook formula (Campbell (2017)), the expected excess return now includes an effect of the cross-currency basis, scaled by the relative risk-weights between asset i and the foreign-currency bond. This result is essentially the "margin-based CCAPM" result of Garleanu and Pedersen (2011), except that we have used a cross-currency basis to measure that shadow value of the constraint and employed Epstein-Zin preferences instead of CRRA utility.

Using the standard approximation for the return of the wealth portfolio (Campbell (2017)), and accounting for the possibility of extra fee income, we have

$$\begin{aligned} E_t[r_{t+1}^w - \ln(f_t^M)] - r_t^b + \frac{1}{2}(\sigma^w)^2 &= \sum_{i \in I} \alpha_t^i (E_t[r_{t+1}^i] - r_t^b + \frac{1}{2}(\sigma^i)^2) \\ &= \frac{\theta}{\psi}\sigma^{wc} + (1-\theta)\sigma^{w^2} + \frac{1}{k^c}|x_{t,1}|. \end{aligned}$$

It follows by the homoskedasticity assumption and the law of iterated expectations that

$$(E_{t+1} - E_t)[r^w_{t+1+j}] = (E_{t+1} - E_t)[r^b_{t+j} + \ln(f^M_{t+j}) + \frac{1}{k^c}|x_{t,1}|].$$

We next combine the log-linear approximation of the intertemporal budget constraint developed by Campbell (1993) and the Euler equation for the consumption-savings decision derived in Lemma 2. These two equations together show that

$$\Delta c^M_{t+1} - E_t[\Delta c^M_{t+1}] = r^w_{t+1} - E_t[r^w_{t+1}] + (1-\psi)\sum_{j=1}^{\infty}\rho^j(E_{t+1}[r^w_{t+1+j}] - E_t[r^w_{t+1+j}]).$$

Note that this formula is identical to a result in Campbell (1993), because the Euler equation for the consumption-savings is not distorted by the regulatory constraint (which only affects the asset allocation).

Plugging our equation for the expected return on the wealth portfolio into this equation, and then the resulting expression for consumption growth into the equation defining the return of an arbitrary asset i (equation (A1)), leads to our main result.

Theorem 3. *The expected arithmetic excess return of an arbitrary asset i can be written as*

$$E_t[r^i_{t+1}] - r^b_t + \frac{1}{2}(\sigma^i)^2 = \gamma\sigma^{iw} + (\gamma - 1)\sigma^{ih} + \frac{k^i}{k^c} sgn(\alpha^i_t)|x_{t,1}|, \tag{A2}$$

where σ^{iw} is the conditional covariance with the wealth portfolio and

$$\sigma^{ih} = Cov_t[r^i_{t+1}, \sum_{j=1}^{\infty}\rho^j(E_{t+1} - E_t)(\frac{1}{k^c}|x_{t+j,1}| + \ln(f^M_{t+j}) + r^b_{t+j})]. \tag{A3}$$

This theorem arrives at the usual conclusion that, if $\gamma > 1$, the manager will be concerned about hedging her investment opportunities, and will demand a risk premium for assets whose returns co-vary with those investment opportunities. Conversely, if $\gamma < 1$, the manager prefers assets whose returns co-vary with her investment opportunities, because those assets allow the manager to better take advantage of those investment opportunities.

Future arbitrage opportunities are a particularly stark example of an investment opportunity, and indicative of the expected returns on the wealth portfolio, and hence returns that negatively co-vary with future arbitrages should have a high risk premium if $\gamma < 1$ and a low risk premium if $\gamma > 1$.

The last piece of our argument is the conjecture (which is verified in the data) that arbitrage opportunities are likely to be persistent. As a result, shocks to the cross-currency basis at time $t+1$ are likely to be indicative of shocks to the arbitrage at later dates. For illustrative purposes only (and ignoring issues about negative numbers), suppose that $|x_{t,1}|$ follows an AR(1) process,

$$|x_{t+1,1}| = \bar{x} + \phi |x_{t,1}| + \sigma^{|x|}\epsilon_{t+1},$$

where ϵ_{t+1} is an I.I.D. standard normal shock. In this case, we have

$$\sum_{j=1}^{\infty} \rho^j (E_{t+1}[\cdot|z_{t+1}] - E[\cdot|z_t]) \frac{1}{k_c} |x_{t+j,1}|) = \frac{1}{k_c} \frac{1}{1-\rho\phi} \sigma^{|x|}\epsilon_{t+1}.$$

Under very strong assumptions (i.e. that borrowing rates r^b_{t+j} and fees f^m_{t+j} are uncorrelated with ϵ_{t+1}), the constant $\frac{1-\gamma}{k_c}\frac{1}{1-\rho\phi}\sigma^{|x|}$ is equal to the value of ξ defined in our hypothesized functional form for the family of log SDFs described in the text. More generally, projecting the revisions in expectations found in Equation (A3) onto the current innovation in the cross-currency basis, under the assumption that such innovations are persistent, generates our hypothesized functional form for the family of log SDFs introduced in Equation (1).

B.1 Proof of Lemma 1

First, observe that diversion does not change α_t^{i*} in the conjectured equilibrium. Consequently, the net benefit of stealing is proportional to

$$\beta R_t^b E_t[V(W_{t+1}^M, z_{t+1})^{-\gamma} V_W(W_{t+1}^M, z_{t+1})](\frac{1}{1+\chi} - \phi_t),$$

and by the usual arguments $V_W(W_{t+1}^M, z_{t+1}) > 0$. If $\frac{1}{1+\chi} > \phi_t$, stealing has a net benefit, and this benefit does not diminish. Consequently, there cannot be a solution with outside equity ($N_t^M > N_t$). Conversely, if $\frac{1}{1+\chi} \leq \phi_t$, diversion has a weakly negative net benefit, and it is without loss of generality to suppose diversion does not occur in equilibrium. By the argument in the main text, it is without loss of generality to suppose $\frac{1}{1+\chi} \leq \phi_t$ and there is no equilibrium stealing.

Now consider a perturbation which increases N_t but shrinks α_t^i so that $\alpha_t^i N_t$ remains constant for all assets. If the household participation constraint does not bind, this generates a strict welfare improvement for the manager and is always feasible. Therefore, the household participation constraint binds,

$$\phi_t N_t(1 - \frac{(1-\phi_t)}{\phi_t} E_t[M_{t+1}^H \sum_{i \in I} \alpha_t^{i*}(R_{t+1}^i - R_t^b)]) = N_t^M.$$

Note by assumption that

$$-1 < E_t[M_{t+1}^H \sum_{i \in I} \alpha_t^{i*}(R_{t+1}^i - R_t^b)] < \frac{1}{\chi} \leq \frac{\phi_t}{1-\phi_t}$$

and hence that positive values of N_t^M and N_t are feasible. Observe that if $N_t^M = N_t = 0$, the manager is taking no risk, which cannot be optimal by the principle of participation. Therefore these values are strictly positive.

Under these assumptions, the manager's fee f_t^M is a function of z_t and ϕ_t,

$$f_t^M(\phi_t, z_t) = \frac{\phi_t}{\phi_t - (1-\phi_t)E[M_{t+1}^H \sum_{i\in I} \alpha_t^{i*}(R_{t+1}^i - R_t^b)|z_t]},$$

Moreover, the manager's final wealth is

$$W_{t+1}^M = R_t^b(W_t^M - C_t^M - N_t^M) + N_t^M f_t^M(\phi_t, z_t)(R_t^b + \sum_{i\in I} \alpha_t^i(R_{t+1}^i - R_t^b)).$$

Note that $f_t^M(\phi_t, z_t)$ is strictly increasing in ϕ_t if $E_t[M_{t+1}^H \sum_{i\in I} \alpha_t^{i*}(R_{t+1}^i - R_t^b)] < 0$ and strictly decreasing if $E_t[M_{t+1}^H \sum_{i\in I} \alpha_t^{i*}(R_{t+1}^i - R_t^b)] > 0$. In the increasing case, we must have $\phi_t^* = 1$ and in this case $f_t^M = 1$; in the decreasing case, $f_t^M \geq 1$, strictly if $E_t[M_{t+1}^H \sum_{i\in I} \alpha_t^{i*}(R_{t+1}^i - R_t^b)] > 0$, and therefore $f_t^M \geq 1$ always. It also follows that ϕ_t^* is purely a function of z_t, and hence the fee f_t^M is also purely a function of z_t.

Now consider a perturbation that increasing N_t^M while scaling down α_t^i so that $N_t^M f_t^M(\phi_t, z_t)\alpha_t^i$ remains constant for all $i \in I$. This perturbation has a weak net benefit, as it increases W_{t+1}^M, and hence it is without loss of generality to suppose $N_t^M = W_t^M - C_t^M$.

We have demonstrated the stated properties conditional in the conjectured that α_t^{i*} is a function only of z_t. We now show that this an equilibrium. We scale variables by wealth. Define $c_t^m = \frac{C_t^M}{W_t^M}$. The problem is

$$V(W_t^M, z_t) = \max_{c_t^M \geq 0, \{\alpha_t^i\}_{i \in I}} \{(W_t^M)^{1-\psi^{-1}}(c_t^M)^{1-\psi^{-1}} + \beta E_t[V(W_{t+1}^M, z_{t+1})^{1-\gamma}]^{\theta^{-1}}\}^{\frac{1}{1-\psi^{-1}}},$$

subject to

$$\frac{W_{t+1}^M}{W_t^M} = f_t^M(z_t) R_t^b (1 - c_t^M) + (1 - c_t^M) f_t^M(z_t) \sum_{i \in I} \alpha_t^i (R_{t+1}^i - R_t^b),$$

$$\sum_{i \in I^c} k^i |\alpha_t^i| \leq 1.$$

We can immediately (following Epstein and Zin (1989)) conjecture and verify that $V(W_t^M, z_t)$ is linear in wealth,

$$V(W_t^M, z_t) = W_t^M J(z_t)$$

for some function $J(z_t)$, and that as a result the optimal policies do not depend on wealth (or any capital structure variables), verifying the conjecture.

B.2 Proof of Lemma 2

Define

$$R_{t+1}^w = f_t^M(z_t)(R_t^b + \sum_{i \in I} \alpha_t^i (R_{t+1}^i - R_t^b)).$$

Using homotheticity, $V(W_t^M, z_t) = W_t^M J(z_t)$, and writing the problem in Lagrangean form,

$$\begin{aligned}
J(z_t) = & \max_{c_t^M \geq 0, \{\alpha_t^i\}_{i \in I}} \min_{\hat{\lambda}_t^{RC} \geq 0} \\
& \{(c_t^M)^{1-\psi^{-1}} + \beta E_t[((1-c_t^M)R_{t+1}^w)^{(1-\gamma)} J(z_{t+1})^{1-\gamma}]^{\theta^{-1}}\}^{\frac{1}{1-\psi^{-1}}} \\
& + \hat{\lambda}_t^{RC}(1 - \sum_{i \in I^c} k^i |\alpha_t^i|).
\end{aligned}$$

The Euler equation is derived in the usual way. Taking the FOC with respect to c_t^M,

$$(c_t^M)^{-\psi^{-1}} = \beta(1-c_t^M)^{-\psi^{-1}} E_t[(R_{t+1}^w)^{(1-\gamma)} J(z_{t+1})^{1-\gamma}]^{\theta^{-1}},$$

and plugging this back into the Bellman equation,

$$\begin{aligned}
J(z_t) &= \{(c_t^M)^{1-\psi^{-1}} + (1-c_t^M)(c_t^M)^{-\psi^{-1}}\}^{\frac{1}{1-\psi^{-1}}} \\
&= \{(c_t^M)^{-\psi^{-1}}\}^{\frac{1}{1-\psi^{-1}}}.
\end{aligned}$$

Therefore, the Euler equation is reads

$$(c_t^M)^{-\psi^{-1}} = \beta(1-c_t^M)^{-\psi^{-1}} E_t[(R_{t+1}^w)^{(1-\gamma)}\{(c_{t+1}^M)^{-\psi^{-1}}\}^{\theta}]^{\theta^{-1}}.$$

We can rearrange this to

$$1 = E_t[(R_{t+1}^w)^{(1-\gamma)}\{\beta(1-c_t^M)^{-\psi^{-1}}(\frac{c_{t+1}^M}{c_t^M})^{-\psi^{-1}}\}^{\frac{1-\gamma}{1-\psi^{-1}}}],$$

and then substitute $c_t^M = \frac{C_t^M}{W_t^M}$ and $c_{t+1}^M = \frac{C_{t+1}^M}{W_{t+1}^M}$,

$$1 = E_t[(R^w_{t+1})^{(1-\gamma)}\{\beta(1-c^M_t)^{-\psi^{-1}}(\frac{W^M_t}{W^M_{t+1}})^{-\psi^{-1}}\frac{C^M_{t+1}}{C^M_t})^{-\psi^{-1}}\}^\theta].$$

Using the budget constraint $\frac{W^M_{t+1}}{W^M_t} = (1-c^M_t)R^w_{t+1}$, we have

$$1 = E_t[(R^w_{t+1})^{(1-\gamma)}\{\beta(R^w_{t+1})^{\psi^{-1}}(\frac{C^M_{t+1}}{C^M_t})^{-\psi^{-1}}\}^\theta].$$

Noting that

$$(1-\gamma)(1+\frac{\psi^{-1}}{1-\psi^{-1}}) = \theta,$$

we conclude that the standard consumption Euler equation applies,

$$1 = E_t[(R^w_{t+1})^\theta\{\beta\frac{C^M_{t+1}}{C^M_t})^{-\psi^{-1}}\}^\theta].$$

The FOC for asset i is

$$\frac{1}{1-\psi^{-1}}\{(c^M_t)^{1-\psi^{-1}} + \beta E_t[((1-c^M_t)R^w_{t+1})^{(1-\gamma)}J(z_{t+1})^{1-\gamma}]^{\theta^{-1}}\}^{\frac{1}{1-\psi^{-1}}-1}\times$$
$$\theta^{-1}(1-\gamma)E_t[\beta^\theta((1-c^M_t)R^w_{t+1})^{(1-\gamma)}J(z_t)^{1-\gamma}]^{\theta^{-1}-1}\times$$
$$(1-c^M_t)^{1-\gamma}E_t[\beta^\theta(R^w_{t+1})^{-\gamma}J(z_{t+1})^{1-\gamma}(R^i_{t+1}-R^b_t)] = \hat{\lambda}^{RC}_t k^c sgn(\alpha^c_t).$$

We can substitute

$$
\begin{aligned}
E_t[\beta^{\theta}(R^{w}_{t+1})^{-\gamma}J(z_{t+1})^{1-\gamma}(R^{i}_{t+1}-R^{b}_{t})] &= \\
(c^{M}_{t})^{-\psi^{-1}\theta}E_t[\beta^{\theta}(R^{w}_{t+1})^{-\gamma}(\frac{c^{M}_{t+1}}{c^{M}_{t}})^{-\psi^{-1}\theta}(R^{i}_{t+1}-R^{b}_{t})] &= \\
(c^{M}_{t})^{-\psi^{-1}\theta}E_t[\beta^{\theta}(R^{w}_{t+1})^{-\gamma}(\frac{W^{M}_{t}}{W^{M}_{t+1}}\frac{C^{M}_{t+1}}{C^{M}_{t}})^{-\psi^{-1}\theta}(R^{i}_{t+1}-R^{b}_{t})] &= \\
(1-c^{M}_{t})^{\psi^{-1}\theta}(c^{M}_{t})^{-\psi^{-1}\theta}E_t[\beta^{\theta}(R^{w}_{t+1})^{\psi^{-1}\theta-\gamma}(\frac{C^{M}_{t+1}}{C^{M}_{t}})^{-\psi^{-1}\theta}(R^{i}_{t+1}-R^{b}_{t})] &= \\
(1-c^{M}_{t})^{\psi^{-1}\theta}(c^{M}_{t})^{-\psi^{-1}\theta}E_t[\beta^{\theta}(R^{w}_{t+1})^{\theta-1}(\frac{C^{M}_{t+1}}{C^{M}_{t}})^{-\psi^{-1}\theta}(R^{i}_{t+1}-R^{b}_{t})]&.
\end{aligned}
$$

Re-scaling $\hat{\lambda}_t$ to λ_t results in the FOC in the lemma,

$$
E_t[\beta^{\theta}(R^{w}_{t+1})^{\theta-1}(\frac{C^{M}_{t+1}}{C^{M}_{t}})^{-\psi^{-1}\theta}(R^{i}_{t+1}-R^{b}_{t})] = \lambda^{RC}_{t}k^{c}sgn(\alpha^{c}_{t}).
$$

C Equivalent definition of the Forward CIP basis

In this section, we show the equivalence between the two definitions for the forward cross-currency basis given by equations (8) and (9), under the assumption of no-arbitrage between forward interest swap rates and term structure of spot interest swap rates.

$$
\begin{aligned}
x_{t,h,\tau} &= r^{\$}_{t,h,\tau} - r^{c}_{t,h,\tau} - \frac{12}{\tau}(f_{t,h+\tau} - f_{t,h}) \\
&= \left(\frac{h+\tau}{\tau} r^{\$}_{t,0,h+\tau} - \frac{h}{\tau} r^{\$}_{t,0,\tau}\right) - \left(\frac{h+\tau}{\tau} r^{c}_{t,0,h+\tau} - \frac{h}{\tau} r^{c}_{t,0,\tau}\right) - \frac{12}{\tau}(f_{t,h+\tau} - f_{t,h}) \\
&= \frac{h+\tau}{\tau}\left[(r^{\$}_{t,0,h+\tau} - r^{c}_{t,0,h+\tau}) - \frac{12}{h+\tau}(f_{t,h+\tau} - s_t)\right] \\
&- \frac{h}{\tau}\left[(r^{\$}_{t,0,h+\tau} - r^{c}_{t,0,h+\tau}) - \frac{12}{\tau}(f_{t,\tau} - s_t)\right] \\
&= \frac{h+\tau}{\tau} x_{t,0,h+\tau} - \frac{h}{\tau} x_{t,0,h},
\end{aligned}
$$

where the second equality follows no arbitrage between forward interest swap rates and the term structure of spot interest swap rates. This no-arbitrage condition likely holds in practice because arbitrage between interest rate derivatives is not strongly affected by most real-world regulatory constraints. It holds in our model under the assumption that derivatives are not subject to the regulatory constraint.

D Profit Calculations

In this section we detail the calculation of profits for the forward CIP trading strategy, and then show how that can be mapped to the cross-currency basis variables we have defined. We will use yen as our example currency.

At time t, the strategy

1. receives fixed (pays floating) on one dollar notional of a h-month forward-starting τ-month interest-rate swap in dollars at annualized fixed rate $R^{\$}_{t,h,\tau}$,

2. enters into a h-month forward agreement to sell $F_{t,h}$ yen in exchange for one dollar,

3. pays fixed (receives floating) on $F_{t,h}$ yen notional of a h-month forward-starting τ-month interest-rate swap in dollars at rate $R^c_{t,h,\tau}$, and

4. enters into a $h+\tau$-month forward agreement to buy $F_{t,h}(R^c_{t,h,\tau})^{\frac{\tau}{12h}}$ yen in exchange for dollars at the exchange rate $F_{t,h+\tau}$.

At time $t+h$, the strategy is unwound. The trader

1. unwinds the receive-fixed dollar swap, earning $(\frac{R^{\$}_{t,h,\tau}}{R^{\$}_{t+h,0,\tau}})^{\frac{\tau}{12h}} - 1$ dollars,

2. cash-settles the h-month forward, earning $\frac{S_{t+h}-F_{t,h}}{S_{t+h}}$ dollars,

3. unwinds the pay-fixed swap, earning $\frac{F_{t,h}}{S_{t+h}}(1-(\frac{R^c_{t,h,\tau}}{R^c_{t+h,0,\tau}})^{\frac{\tau}{12h}})$ dollars, and

4. unwinds the $h+\tau$-month forward, earning $(\frac{1}{F_{t+h,\tau}} - \frac{1}{F_{t,h+\tau}})\frac{F_{t,h}(R^c_{t,h,\tau})^{\frac{\tau}{12h}}}{(R^{\$}_{t+h,0,\tau})^{\frac{\tau}{12h}}}$.

In this last expression, we have used $R^{\$}_{t+h,0,\tau}$ as the discount rate on the forward profits (converted to dollars). In our model, because derivatives are unaffected by the regulatory constraint, the dollar risk-free rate is in indeed the correct discount rate for the forward profits. If net derivative profits affected the regulatory constraint, the appropriate discount rate would depend on questions like whether the trader could unwind or net the derivatives instead of simply taking an offsetting position. However, as a practical matter, the choice of discount rate has a minuscule effect on the computed profits.

Therefore, total profit per dollar notional (i.e. the excess return) is

$$\Pi^c_{t+h,h,\tau} = (\frac{R^{\$}_{t,h,\tau}}{R^{\$}_{t+h,0,\tau}})^{\frac{\tau}{12h}} - \frac{F_{t,h}}{S_{t+h}}(\frac{R^c_{t,h,\tau}}{R^c_{t+h,0,\tau}})^{\frac{\tau}{12h}} + (\frac{1}{F_{t+h,\tau}} - \frac{1}{F_{t,h+\tau}})(\frac{R^c_{t,h,\tau}}{R^{\$}_{t+h,0,\tau}})^{\frac{\tau}{12h}} F_{t,h}.$$

Recall the definition of the cross-currency basis,

$$(R^c_{t+h,0,\tau})^{\frac{\tau}{12h}} S_{t+h} = \frac{(R^{\$}_{t+h,0,\tau})^{\frac{\tau}{12h}} F_{t+h,\tau}}{(1 + X^c_{t+h,0,\tau})^{\frac{\tau}{12h}}}$$

and

$$(R^c_{t,h,\tau})^{\frac{\tau}{12h}} F_{t,h} = \frac{(R^{\$}_{t,h,\tau})^{\frac{\tau}{12h}} F_{t,h+\tau}}{(1 + X^c_{t,h,\tau})^{\frac{\tau}{12h}}}.$$

Plugging in these definitions,

$$\Pi^c_{t+h,h,\tau} = (\frac{R^{\$}_{t,h,\tau}}{R^{\$}_{t+h,0,\tau}})^{\frac{\tau}{12h}} \left\{ 1 - \frac{F_{t,h+\tau}}{F_{t+h,\tau}} (\frac{1 + X^c_{t+h,0,\tau}}{1 + X^c_{t,h,\tau}})^{\frac{\tau}{12h}} + (\frac{F_{t,h+\tau}}{F_{t+h,\tau}} - 1) \frac{1}{(1 + X^c_{t,h,\tau})^{\frac{\tau}{12h}}} \right\}.$$

This exact profit formula is complicated by a variety of discounting effects that arise in the presence of arbitrage. Note, however, that all of these effects (deviations of interest rates and forward exchange rates from their previous forward values) are typically at most a few hundred basis points. In the presence of cross-currency basis values that on the order of basis points, these discounting effects will be a couple percent of some basis points, and hence for the most part negligible.

We therefore employ a first-order approximation. Define

$$\begin{aligned} \epsilon^F_{t+h,h,\tau} &= \ln(\frac{F_{t+h,\tau}}{F_{t,h+\tau}}), \\ \epsilon^R_{t+h,h,\tau} &= \ln(\frac{R^{\$}_{t+h,\tau}}{R^{\$}_{t,h,\tau}}). \end{aligned}$$

Taking a first-order expansion around $x^c_{t,h,\tau} = x^c_{t+h,\tau} = \epsilon^F_{t+h,h,\tau} = \epsilon^R_{t+h,h,\tau} = 0$, we have

$$\Pi^c_{t+h,h,\tau} \approx \pi^c_{t+h,h,\tau} = \frac{\tau}{12h}(x^c_{t,h,\tau} - x^c_{t+h,0,\tau}).$$

Annualizing these monthly profits gives the formula employed in the main text.

E Forward CIP Trading Strategy's Return Predictability

In this Internet Appendix section, we consider whether the returns of our forward CIP trading strategy are predictable. In the context of the model, as usual, return predictability implies time variation in either the quantity or price of cross-currency basis risk.[54]

We find evidence that the level of the basis predicts the return of the forward CIP trading strategy, and suggestive but not definitive evidence that the slope of the forward CIP trading strategy "term structure" also predicts returns. The former is consistent with our finding that risk premia are higher on quarter ends, and with the intuition that when constraints are tight, the risk that they tighten further is higher. This might be expected on the grounds that tighter intermediary constraints tend to coincide with higher levels of risk premia (a point emphasized in the intermediary asset pricing literature, for example in He and Krishnamurthy (2011)). The latter is analogous to findings of return predictability in the term structure literature (e.g. Campbell and Shiller (1991)).

The statistical significance of our results on the slope varies across specifications, and depending on whether or not the data sample includes the COVID-19 crisis. For this reason, we view these results as suggestive rather than definitive.

The return predictability regressions we run are presented in Internet Appendix Tables

[54] In Internet Appendix F, we explore a different kind of predictability, related to quarter-end effects.

A10 (full post-GFC sample) and A11 (post-GFC, pre-2020). The regressions estimate equations of the form

$$x^c_{t,h,\tau} - x^c_{t+h,0,\tau} = \alpha + \beta(x^c_{t,h,\tau} - x^c_{t,0,\tau}) + \gamma x^c_{t,0,\tau} + \epsilon_{t+h}, \tag{A4}$$

where some of α, β, and γ may be set to zero. We use three-month tenors ($\tau = 3$) and look at one-month forward differences between the forward basis and the spot basis that is actually realized ($h = 1$). We use the "classic carry" AUD-JPY basis in all regressions (this avoids the need to define a spot basis or slope for our "First PC" portfolio). We estimate the regressions in monthly data. Note that our outcome variable is not exactly the profit per dollar notional defined in equation (11), because we do not scale the outcome variable by the duration $\frac{\tau}{12}$. This is analogous to regressing yield changes on yields instead of price changes on yields.

The first column of Table A10 simply regresses the outcome variable on a constant. We estimate an unconditional mean of 6.2 basis points and a root mean squared error of 12.5 basis points. In other words, on average, the one-month forward implied three-month classic carry basis is 6.2 basis points higher than the spot three-month basis one month in the future.

The next four columns of Table A10 present the estimations of equation (A4) with various coefficients restricted to zero. The specifications without the constant have the appealing property that, in a world in which both the spot and forward bases are zero (covered interest parity holds), we should expect no return on our forward CIP trading strategy. In the full sample, our estimate for the slope coefficient is positive but statistically insignificant, and our estimate for the basis coefficient is significant at the 5% level.

In the pre-2020 sample (Table A11), which excludes the COVID-19 crisis, both coefficients are statistically significant. During March 2020, both of the predictor variables in our regression (the slope and the spot basis) reached extreme values. Our regression results are thus (unsurprisingly) somewhat sensitive to the include of this time period.

One concern with using the spread as a predictor for the forward CIP return is that the forward basis $x^c_{t,h,\tau}$ enters both sides of equation (A4), and is surely measured with some bid-offer induced noise. This issue is exactly analogous to the role of a price in a regression of return on lagged return (as in Roll (1984)). A standard approach to dealing with these issues is to avoid using the current value of the forward basis as a predictor value, and replace it with a lagged value instead (see, e.g., Jegadeesh (1990)). We adopt this approach, employing a lagged value of the spread, $x^c_{t-k,h,\tau} - x^c_{t-k,\tau}$, as an instrument for the current value of the spread. Columns (6), (7), and (8) of Table A10 repeat the specifications of columns (2), (3), and (4), using a spread lagged by one business day as an instrument for the current spread value. Our point estimates remain similar across specifications, and the lagged spread is reasonably predictive of the current spread (as measured by the 1st stage F statistic). We should emphasize that this lag approach is not a panacea (Jegadeesh and Titman (1995)). We have no theory on what causes the spread to vary over time, and hence cannot say decisively that the "real" variation dominates the micro-structure induced variation over a one or two-week period.

F Overnight (ON) and Tomorrow/Next (TN) CIP Deviations

In this Internet Appendix, we demonstrate how to calculate ON and TN CIP deviations. The standard formula for spot and forward CIP deviations (equations (6) and (8) in the paper) do not apply for these short-dated deviations because the spot exchange rate generally settles with T+2 convention, making the spot contract effectively a two-day forward contract. The ON calculation follows the formula in Correa et al. (2020). We use central bank deposit rates as the cash market interest rates, as these administered rates do to change outside central bank meetings. We use spot exchange rates and ON and TN forward points from Bloomberg <BFIX> based on quotes at 8:00 AM New York time.

To calculate the ON CIP deviation, we use the following formula:

$$x^{ON} = ((1 + r * N^{ON}/d) * (S - \phi_{TN}/D)/(S - \phi_{TN}/D - \phi_{ON}/D) - 1) * (d/N^{ON}) - r^{\$},$$

where r is the foreign interest rate on foreign central bank deposit, $r^{\$}$ is the interest on reserves paid by the Federal Reserve, S is the spot exchange rate (defined as units of foreign currency per dollar), ϕ_{TN} and ϕ_{ON} are the forward points on the ON and TN contracts, respectively, $d = 360$ is the day count convention, D is the forward point multiplier (10000 for EUR and CHF, and 100 for JPY), and N^{ON} is the number of calendar days between the trading date and the ON contract settlement date (T+1).

To calculate the TN CIP deviation, we use the following formula:

$$x^{TN} = ((1 + r * N^{TN}/d)/S * (S - \phi_{TN}/D) - 1) * (d/N^{TN}) - r^{\$},$$

where N^{TN} is the number of calendar days from between the ON contract settlement date (T+1) and the TN contract settlement date (T+2).

G Definitions of Other Near-Arbitrages

We define the seven near-arbitrages as follows.

- **Bond-CDS basis**: the spread between the yield on the 5-year North America investment grade bonds over their corresponding credit default swaps (CDS). The series is from the J.P. Morgan Markets DataQuery.

- **CDS-CDX basis**: the spread between the composite of 125 single-name CDS spreads in the North America investment grade credit default swap index (CDX.NA.IG) and the quoted spread on the CDX.NA.IG. The series is from the J.P. Morgan Markets DataQuery.

- **US Libor tenor basis**: the spread in fixed rates between a 5-year interest rate swap indexed to one-month US Libor and a 5-year interest rate swap indexed to three-month US dollar Libor. The series is from the J.P. Morgan Markets DataQuery.

- **Swap-Treasury spread**: the spread between the 30-year US Libor interest swap rate and the 30-year US Treasury yield. The series is from Bloomberg.

- **Refco-Treasury spread**: the spread between the yield on the 5-year resolution funding corporation strip (fully backed by the U.S. government) and the 5-year US Treasury bond. The series is from Bloomberg.

- **KfW-Bund spread**: the spread between the yield on the 5-year euro-denominated bonds issued by Kreditanstalt für Wiederaufbau (fully backed by the German government) and the 5-year German bund yield. The series is from Bloomberg.

- **TIPS-Treasury spread**: the spread between the yield on the asset swap package combining a 5-year Treasury bond and an inflation swap and the yield on the 5-year Treasury inflation protected security (TIPS). The series is from Bloomberg.

In Internet Appendix Table A31, we summarize the mean and standard deviation of these near-arbitrages, together with the AUD-JPY spot cross-currency basis, by the pre-GFC, GFC and post-GFC period.

H Estimating the SDF from Prices of Risk

Our hypothesized SDF (Equation (1)) postulates that $m_{t+1} = \mu_t - \gamma r^w_{t+1} + \xi |x_{t+1,1}|$. Let $\lambda = [\lambda_{r_w}, \lambda_{|x|}]$ be the price of risk on the two factors, the wealth portfolio return and the magnitude of the cross-currency basis, respectively, and Σ be the variance-covariance matrix between these two factors. We can estimate the SDF parameters as[55]

$$\begin{bmatrix} \gamma \\ \xi \end{bmatrix} = \Sigma^{-1} \begin{bmatrix} \lambda_{r_w} \\ \lambda_{|x|} \end{bmatrix}.$$

The parameter λ is proportional to the single regression coefficient of the true SDF on the two factors. It therefore can be estimated from the realized market risk premium on the two factor's factor-mimicking portfolios. If we use the He et al. (2017) value-weighted intermediary return on equity as the factor-mimicking portfolio for intermediary wealth returns, and use the returns on the forward CIP trading strategy as a direct measure of the risk premium on the cross-currency basis, then we can estimate λ and, by extension, the SDF parameters γ and ξ.

We estimate the price of risk on intermediary equity return from monthly excess returns from January 1970 to August 2018, the longest panel of returns that we have. The average monthly excess return is about 0.59%, which implies an annual excess return of about 7.3%.

[55] The signs in this equation are slightly non-standard. The factor in the SDF is $-|x_{t+1}|$, and the forward CIP return is positive when this factor increases (i.e. the basis shrinks).

We estimate the price of risk on the forward CIP trading strategy from the Post-GFC sample. Given the short sample, we use daily observations of the monthly returns on the 1M-forward 3M "Top-Six First PC" forward CIP trading strategy. The average monthly return is 4.6 basis points, which corresponds to an annual profit of 13.8 basis points on the notional.

To calculate the SDF parameters, we also need the variance-covariance between the two factors. We estimate Σ using monthly returns on the intermediary equity and the 1M-forward 3M AUD-JPY forward CIP trading strategy in the Post-GFC period (July 2010 to December 2020). Together with estimates of λ, we find an estimate of γ of -0.155 and an estimate of ξ of 247. While the estimate of a positive ξ is statistically significant at conventional significance levels, the estimate of γ is imprecise, and we cannot reject that the true γ is greater than 1. We summarize these results in Internet Appendix Table A32.

I Cross-Sectional Asset Pricing with HKM and AEM Factors

In Internet Appendix Tables A15, A16, A17, and A18, we run two-factor models involving the Market and an intermediary-related factor (the HKM factor, the HKM intermediary equity return, the AEM broker-dealer leverage factor, and the forward CIP return PC1, respectively). The first three of these specifications do not include the forward CIP return, and are therefore use betas estimated from the full data sample (including pre-GFC data). We find (consistent with results in HKM) that the AEM factor helps price equities[56] but it not priced consistently across the other asset classes, and when pooling asset classes has a roughly zero risk price. When pooling asset classes for the two HKM factors, we find coefficient estimates that are attenuated relative to the results of HKM (a result caused in part due

[56]Specifically, the AEM model has a relatively low mean average pricing error for the FF6 asset class, after accounting for the difference between monthly and quarterly data specifications.

to differences in the sample and in part due to differences in the asset class definitions). As a result, the prices of the two HKM factors cannot be statistically distinguished from zero; however, the point estimate for the risk price of the intermediary equity return exceeds the directly estimates price of risk. These two results taken together suggest that our cross-sectional analysis with the HKM factors lacks power, despite using the full sample of available returns. In contrast, our results for the forward CIP return and the market factor (Table A18) involve a price of risk for the forward CIP return that is consistent across asset classes and statistically distinguishable from zero when pooling asset classes. We find again when pooling across asset classes that we cannot reject our "H1" hypothesis. Relative to the HKM factors, using the forward CIP return results in smaller pricing errors for options, CDS, and commodities, but a higher pricing error for US bonds.

Internet Appendix Table A19 presents results that use the market, intermediary equity, and forward CIP return factors. Our H1 hypothesis now requires that all three risk prices be consistent with the mean excess returns of those tradable factors. We again are unable to reject this hypothesis in our pooled specification. Internet Appendix Table A20 presents a versions of Table 8 that does not include the basis shock (i.e. a specification found in HKM). The point estimates for the price of intermediary equity risk are again generally higher than our direct estimate of the intermediary equity risk premium. We interpret this result as again suggesting that either the basis shock is captures something about intermediary wealth that the equity return omits or that it captures an intertemporal hedging consideration that is significant in its own right.

J Bayesian Test of Asset Pricing Models

In this Internet Appendix section we describe the Bayesian asset pricing methodology of Barillas and Shanken (2018) and Chib et al. (2020).

Let M_j be a candidate factor model and $\mathcal{ML}_j$ be the marginal likelihood of M_j. The posterior probability of observing a model is

$$P(M_j|Data) = \{\mathcal{ML}_j \times P(M_j)\} \times \left\{\sum_i \mathcal{ML}_i \times P(M_i)\right\}^{-1},$$

where the denominator sums across all models under consideration.

Which models are compared? Consider a set of n factors, at most one of which is non-tradable. If there is a non-tradable factor, treat it is a "baseline factor" present in all specifications. The remaining tradable factors could be included in the factor model (f) or excluded (f^*), in which case they are treated as test assets. For example, in the first specification in Table 7, the factors are the market, Fwd CIP, and intermediary equity returns. The exercise compares models with one, two, or all three of these factors.

For each model M_j, the marginal likelihood is

$$\mathcal{ML}_j = P(R|f) = \int\int P(R|f, \alpha, \beta, \Sigma) P(\alpha|\beta, \Sigma) P(\beta, \Sigma) d\alpha d\beta d\Sigma,$$

where R is the excess returns of the test assets (f^*), f are the factors included in model M_j, and α, β, and Σ are from

$$R_t = \alpha + \beta f_t + \Sigma \epsilon_t.$$

Here, the regression residuals ϵ_t are assumed to be IID across time and normally distributed.

Barillas and Shanken (2018) suggest the prior that all models are equally likely ex-ante ($P(M_j) = P(M_{j'})$), and construct a prior $P(\alpha|\beta, \Sigma)$ based on bounds for Sharpe ratios. Using these priors and an appropriately constructed improper prior for the nuisance parameters $P(\beta, \Sigma)$ (Chib et al. (2020)), we can compute the relative likelihood of each candidate model M_j, $P(M_j|Data)$. We implement this procedure using the software of Chib et al. (2020).

These probabilities depend primarily on the Sharpe ratios of the excluded factors f^* given the factor model (f_0, f). If model M_j with only f is sufficient, then α^* from $f_t^* = \alpha^* + \beta^* f + \epsilon^*$ should be 0. In other words, the marginal likelihood of a model is high when the model is correctly specified relative to the set of available potential factors.

K Cross-Sectional Asset Pricing Details

In this Internet Appendix section, we provide more details about the cross-sectional asset pricing exercise of Section 4. We begin by describing our test asset portfolios, then discuss the differences between our exercise and He et al. (2017) (HKM).

Internet Appendix Tables A15, A16, and A20 show cross-sectional asset pricing results for our test asset classes with the HKM factors. These tables can be compared (noting the differences in asset class definitions and sample) with Tables 14 and 17 of He et al. (2017).

K.1 Factors and Test Assets

As discussed in the main text, our choice of test assets is inspired by HKM, but for various reasons the exact portfolios we use in each asset class differ slightly from their counterparts in HKM. Below, we describe the data used for each asset class. We truncate all of our series at the end of December 2020.

The Market and the Risk-Free Rate

The equity return we use is the Market factor provided on Ken French's website (originally from CRSP). We also use, for most of our sample, the 1-month t-bill rate provided on Ken French's website (and due to Ibbotson and Associates, Inc.). These are the same data sources used by HKM. However, as discussed on Ken French's website, the Market return was changed in October 2012 and as a result there are some differences between our series and the one originally used by HKM.

We also adjust the risk-free rate to use one-month OIS swap rates instead of 1-month t-bill rates once the data becomes available. We make this adjustment to be consistent with the risk-free rates we used to compute the cross-currency basis and forward CIP returns. This adjustment has a minimal impact on our results.

The HKM Intermediary Wealth Returns

In our equity-return only specification (Table 8), we use as an equity return the "intermediary value-weighted investment return" of HKM, obtained from Asaf Manela's website. When we use the original HKM specification, perhaps augmented with our basis shock (Internet Appendix Tables A15 and A21), we use our market return described above and the "intermediary capital risk factor" of HKM, obtained from Asaf Manela's website.

The AEM Leverage Constraint

We follow the Adrian et al. (2014) and calculate the AEM factor as the seasonally adjusted quarterly change in the log of the broker-dealers' leverage ratio. The leverage ratio is calculated as the ratio of the book equity over total assets of the broker-dealer sector from Flow of Funds, or BOGZ1FL664090005Q (Assets)/(BOGZ1FL664090005Q (Assets) -

BOGZ1FL664190005Q (Total Liabilities)). The seasonal adjustment is done by removing fixed-effects associated with the the quarterly dummies using a backward-looking rolling window beginning in 1965Q3. Our constructed series is 99% correlated with the original series used in Adrian et al. (2014) for the overlapping sample period.

Equities (FF6)

Our test equity portfolios are the monthly return series of the "6 Portfolios Formed on Size and Book-to-Market (2x3)" available on Ken French's website, building on Fama and French (1993). The series begins in July 1926.

HKM use the 25 portfolio version of these series, with data from 1970 onwards. We use six portfolios instead of twenty five to mitigate the possibility of spurious results arising from the presence of large bank stocks on both sides of the regression. This issue causes, in our post-crisis sample, an unusually strong correlation between the HKM intermediary value-weighted investment return and one particular Size-by-Value 25 portfolio (Large Value). Using only six portfolios instead of twenty five allows us to capture the factor structure of equity returns documented by Fama and French (1993) while mitigating this issue.

There also appear to be a variety of small differences between the returns we obtained from Ken French's website in 2021 and the returns HKM obtained in 2012. Many of these differences are small enough that they can be attributed to rounding, but some are not. Ken French's website does mention a variety of changes in CRSP between 2012 and the present, but none seem directly applicable to the size-and-value portfolios.

US Bonds (US)

Our U.S. bond portfolios include both government and corporate bonds. The government bonds are the five CRSP "Fama Maturity Portfolios" defined in twelve-month intervals, plus the two longer-maturity portfolios (60-120 months and >120 months). We drop the shortest maturity portfolio, because of the similarity between its returns and the risk-free rate, and end up with six government bond portfolios. The corporate bonds are five Bloomberg corporate bond indices, which correspond to US corporate bonds with ratings of AAA, AA, A, B, and high yield.[57]

To include the returns for a particular month, we require that the returns for all six government bond maturity buckets and all five corporate bond indices be available. As a result, our data starts in September 1988. Four of our government portfolios are groupings of the Fama bond portfolios studied by HKM, who use the six-month interval portfolios and do not exclude the shortest maturities or include the longer maturity portfolios. Our corporate bond indices are different from the ones studied by HKM, and were chosen because they are readily available.

Sovereign Bonds (Sov)

Our sovereign bond portfolio construction follows the procedure of Borri and Verdelhan (2015). Those authors consider all countries in the JP Morgan EMBI index, and sort bonds into six portfolios. They first divide countries into two groups, depending on whether their bonds have a low or high beta to US equity market returns, and then within each of these groups split bonds into three sub-groups based on their S&P rating. HKM use exactly the

[57] The tickers are LU3ATRUU Index, LU2ATRUU Index, LU1ATRUU Index, LUBATRUU Index, and LF98TRUU Index.

data of Borri and Verdelhan (2015), as those two papers are roughly contemporaneous.

We implement this procedure with updated data. However, several countries have been dropped from the EMBI index, and do not have returns available for the post-crisis period. These countries are omitted from our entire analysis, and as a result there is an imperfect (80%) correlation between our portfolio returns and the original Borri and Verdelhan (2015) returns.

Foreign Exchange Portfolios (FX)

We use the 11 forward-premium-sorted portfolios of Lustig et al. (2011). These portfolios consist of up to 34 currencies on each date. Six these portfolios contain all currencies, sorted by forward premia. Five contain only developed-country currencies, sorted by forward premia. These returns series are updated regularly and provided to us by Adrien Verdelhan.

In contrast, HKM use six portfolios sorted by forward premia from Menkhoff et al. (2012) and six portfolios sorted by interest rate differential from Lettau et al. (2014).[58] Because covered interest parity holds for most of the sample, these two groups of portfolios should be essentially identical. However, the two papers differ on data sources and samples (Menkhoff et al. (2012) have up to 48 currencies from 1983 to 2009, Lettau et al. (2014) have up to 53 from 1974 to 2010), and consequently the two sets of portfolios to do not exactly span each other.

Equity Options Portfolios (Opt)

We construct equity options portfolios using the procedure of Constantinides et al. (2013) to generate portfolios of puts and calls sorted by moneyness and maturity. We form twelve

[58]The published version of Menkhoff et al. (2012) describes only five portfolios, and two other portfolios that are linear combinations of the five.

portfolios (six of calls and six of puts), for two different maturities (30-day and 90-day), and three different levels of moneyness (in-, at-, and out-of-the-money). The underlying data source is OptionMetrics via WRDS. A previous version of this paper also used 60-day expiry options; omitting them has a minimal impact on the results.

The OptionMetrics data needs to be cleaned extensively, as discussed at length in Constantinides et al. (2013). We follow their procedure as closely as feasible and are able to construct portfolios whose returns closely track the portfolios of Constantinides et al. (2013) in their original sample.

HKM use 18 portfolios based on the original portfolios of Constantinides et al. (2013). However, they use nine different moneyness levels for calls and puts, collapsing the three different maturities into a single portfolio for each moneyness. We have found that collapsing into moneyness-by-maturity buckets reduces the correlation between the return series.

We follow Constantinides et al. (2013) in "leverage-adjusting" the option portfolio returns by mixing the original return with some amount of the risk-free return to ensure that the Black-Scholes-implied beta to the market of each portfolio is one. The advantage of this approach is that the return distribution of the options is closer to normal. The disadvantage of this approach is that, by construction, all of the option portfolios have a beta to the Market factor that is close to one. This can lead to weak identification, as can be seen in the KZ p-value of column (4) in Internet Appendix Table A19. In the pooled specification (column (9) of that table), other assets help identify the price of Market risk. In our main specification (Table 8), the Market is not included as a factor, and this particular weak identification problem does not arise.

Credit Default Swaps (CDS)

Our CDS returns series consists of returns for five major CDS indices. The indices are CDX.NA.IG (North American investment grade), CDX.NA.HY (North American high yield), CDX.NA.XO (North American cross-over, between investment grade and high-yield), CDX.EM (emerging markets), and iTraxx Europe. These indices are available from Markit and via Bloomberg, with all five series having data from July 2004 onwards.

In contrast, HKM use portfolios of single name CDS returns constructed from Markit data on single-name CDS. We obtained this data and attempted to construct similar portfolios, but were unable to approximately match the return series used by HKM. Using the index returns instead of the single name returns reduces the likelihood of errors in our calculations and should make it easier for other researchers to replicate our results.

Commodity Futures (Comm)

We use six commodity return indices constructed by Bloomberg, covering energy, grains, precious metals, industrial metals, livestock, and "softs". We obtain the total return index for each commodity index from Bloomberg. These indices aggregate the returns of several short-maturity futures for each commodity. All of the index returns are available starting in February 1991.

HKM instead build on the work of Yang (2013) and use twenty three commodities. HKM also use data from the Commodities Research Bureau, which has the advantage of going back further in time, and use a slightly different method of aggregating the various short-maturity futures contract returns into a single index for each commodity.

We use the Bloomberg commodity indices for two reasons. First, to facilitate pooling across assets, it is convenient to have a smaller number of test assets in each asset class (to avoid N close to T in the pooled specification). Second, Bloomberg indices are designed to ensure each of the commodities included in the index is sufficiently liquid and frequently traded. Several of the commodities in the original HKM data set (e.g. oats, rice, palladium) are not liquid enough to be included in the Bloomberg indices.

An earlier version of this paper instead followed the HKM approach. The resulting point estimates for the two groups of commodities are in some cases quite different; however, for both the six indices and twenty three commodities, the cross-sectional results are poorly identified (high KZ p-values) and have large standard errors (which, due to the lack of identification, likely understate the true degree of uncertainty).

OIS and IBOR Forward CIP Returns (FwdCIP)

We use OIS and IBOR forward CIP returns in six currencies (CAD, GBP, EUR, CHF, AUD, JPY) vs. USD as test assets. We exclude the 3m OIS AUD and JPY, which we used to construct the Classic Carry forward CIP returns and are highly correlated with the first PC of the forward CIP returns, our proposed factor in the SDF. Our OIS returns include both 1-month forward 1-month and 1-month forward 3-month returns, whereas the IBOR returns are restricted to 3-month tenors due a lack of available data.

For all of these assets, we study as an excess return

$$x^c_{t,h,\tau} - x^c_{t+h,0,\tau},$$

which is the profit per dollar notional, normalized by the duration.

We construct the OIS forward CIP returns as described in the text. IBOR forward CIP returns are constructed in an essentially identical fashion, using 3M spot IBOR rates and

FRA agreements with 3M IBOR as the underlying rate. For all returns, we consider only the post-crisis period.

We exclude CHF OIS returns due to problems with the OIS data (and hence use only IBOR for CHF), and exclude CAD IBOR returns due to missing data (and hence use only OIS returns for CAD). As a result, we combine five IBOR-based forward CIP returns with five OIS-based one-month tenor and three OIS-based three-month tenor forward CIP returns, for a total of thirteen test assets.

K.2 Estimation and Standard Errors

Our analysis is the GMM version of a traditional two-pass regression to estimate the price of various risk-factors, as described in chapter 12 of Cochrane (2009). Our point estimate come from an exactly identified single-step GMM estimation procedure, as described on pages 241-243 of Cochrane (2009). We use a Newey-West kernel with a twelve-month bandwidth (Newey and West (1987)) to construct standard errors that are robust to heteroskedasticity and auto-correlation.

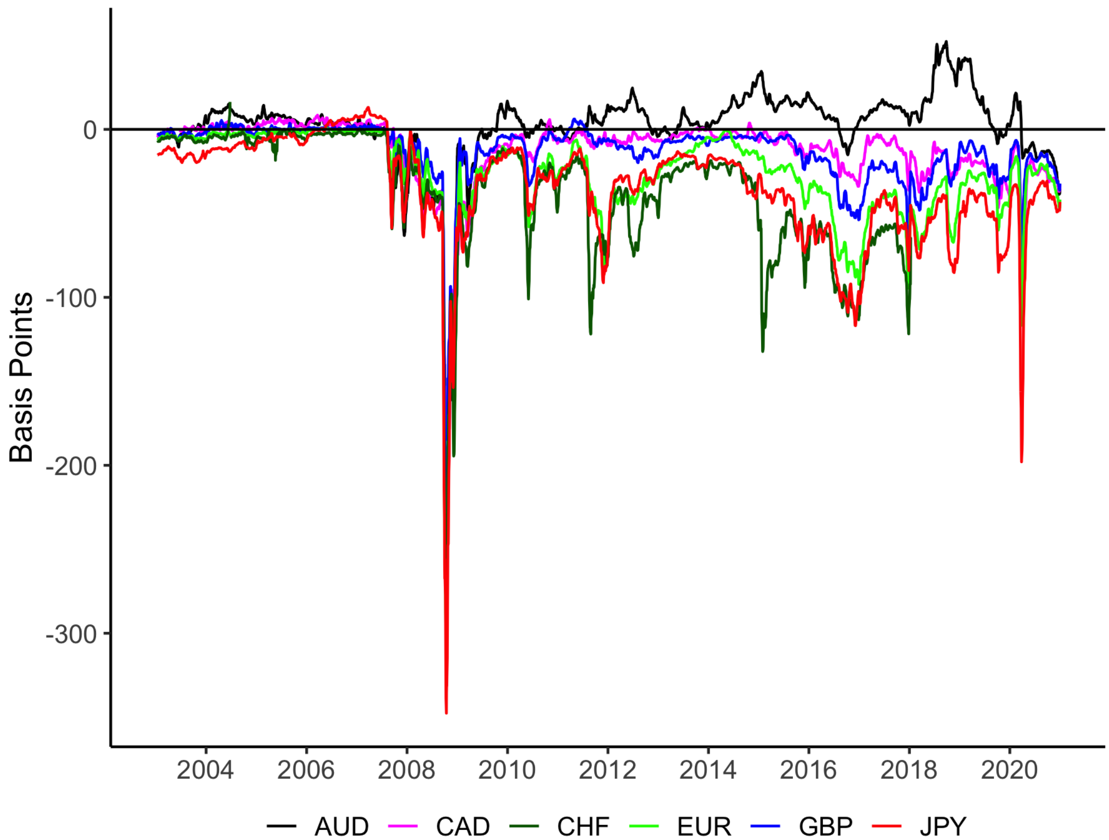
The one key difference between our procedure and the textbook procedure is that we allow the samples for the estimation of the betas and the means to differ.[59] To implement this, we introduce as parameters in our GMM equations a mean-return parameter for each asset and an extra equation for each asset stating that the difference of the mean parameter and the asset excess return is zero in expectation. We then write our cross-sectional asset pricing equation (12) entirely as a function of parameters, with no data. These changes, and allowing our GMM estimator to use different samples for different equations, implement the

[59] For this reason, we do not use an automatic bandwidth selection procedure for our standard errors. We have found that the standard errors are insensitive to the bandwidth choice, likely because returns exhibit small amounts of auto-correlation.

desired outcome that the mean and beta samples can differ.

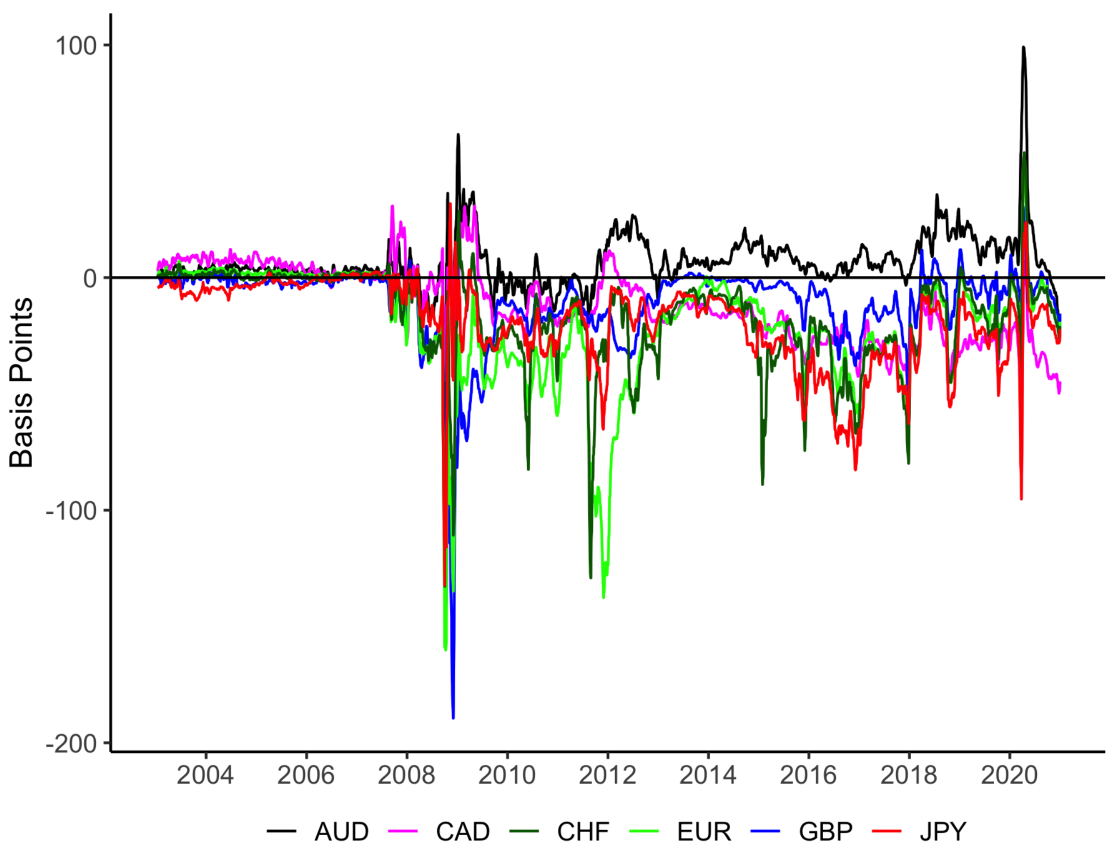
L Additional Figures and Tables

Figure A1: **Three-month OIS-based Cross-Currency Bases**



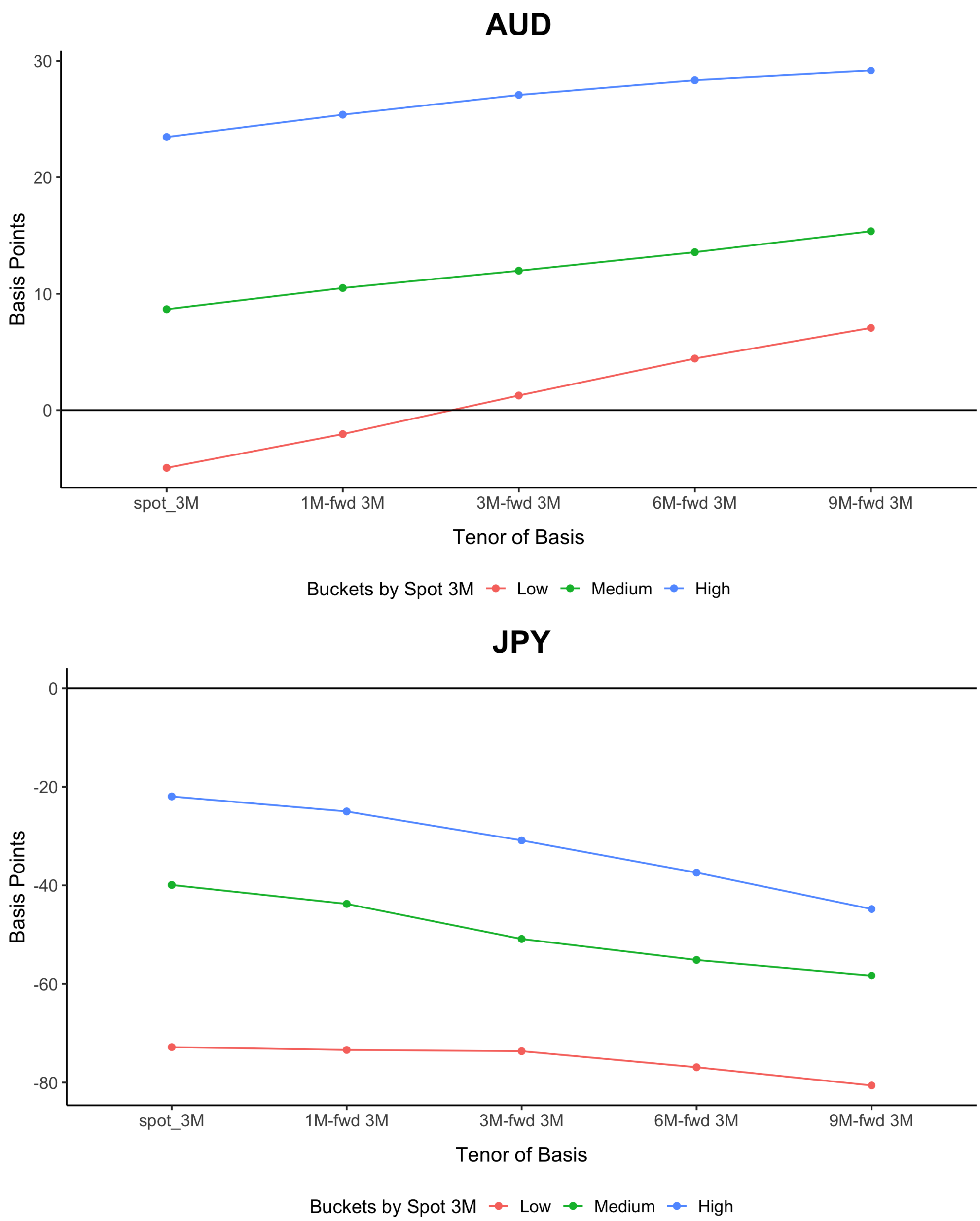
Notes: This figure plots the 10-day moving average of daily spot 3M OIS cross-currency basis vis-à-vis the USD, measured in basis points, for the six sample currencies. The spot OIS basis is $x^c_{t,0,3}$, as defined in Equation (6).

Figure A2: **Three-month IBOR-based Cross-Currency Bases**



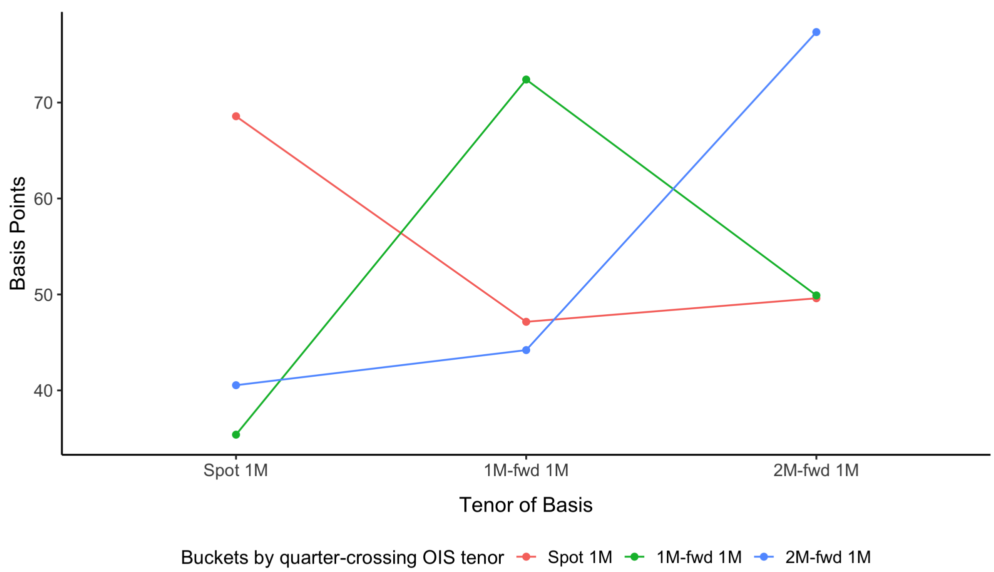
Notes: This figure plots the 10-day moving average of daily spot 3M IBOR cross-currency basis vis-à-vis the USD, measured in bps, for the six sample currencies. The spot IBOR basis is $x^c_{t,0,3}$, as defined in Equation (6).

Figure A3: **Term Structure of the Forward Cross-Currency Basis (Alternative Forward Tenors)**



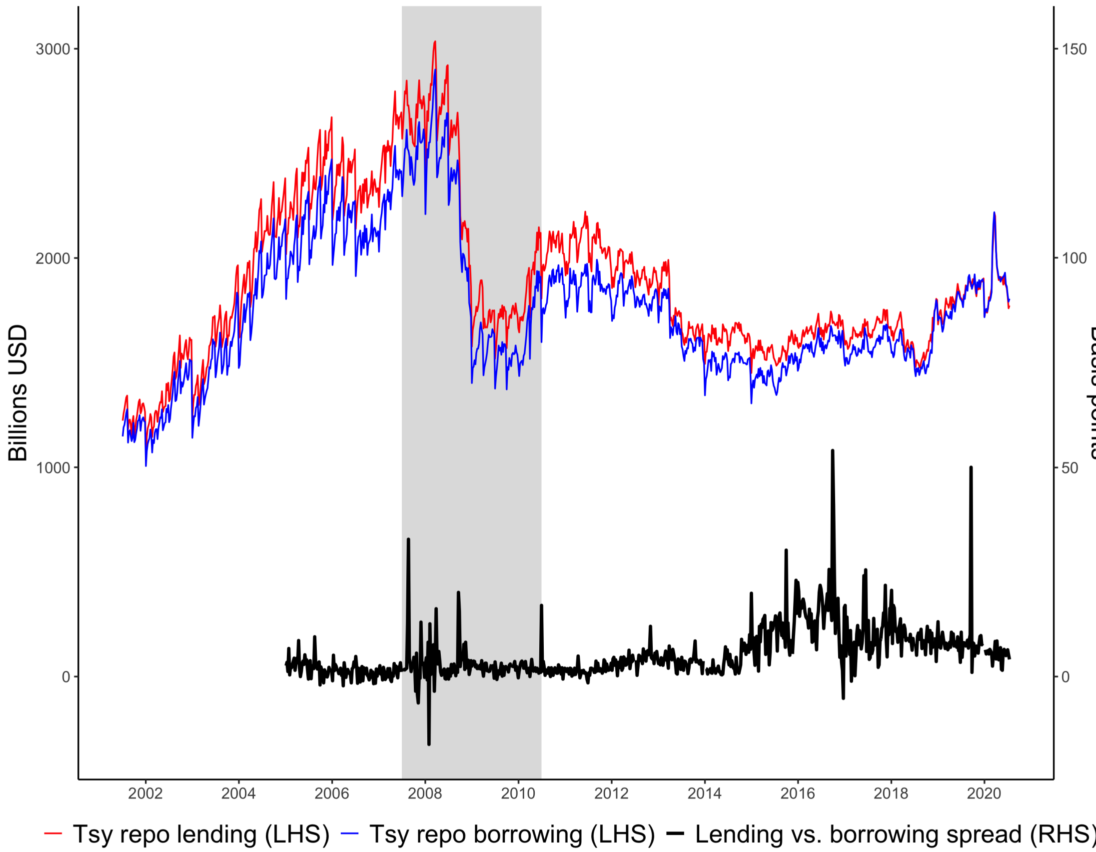
Notes: This figure illustrates the time series average spot and forward-starting cross-currency bases in AUD and JPY, vis-à-vis the USD, as defined in Equation (8). For each currency, the sample from July 2010 to December 2020 is split into three sub-samples based on the tercile of the level of the spot 3M OIS cross-currency basis. Within each sub-sample, the time series average of the relevant spot/forward OIS cross-currency basis is shown. Compared to Figure 2, this Figure plots a different set of forward tenors and use only OIS contracts of 3M tenor.

Figure A4: **Quarter-end-crossing in spot and forward cross-currency bases**



Notes: This figure illustrates the time series average of spot, 1M-forward 1M, and 2M-forward 1M AUD-JPY cross-currency bases. The sample from July 2010 to December 2020 is split into three sub-samples based which of the three bases has its OIS interest tenor crossing the quarter end. The three lines correspond to the three sub-samples, and each point shows the time series averages of the OIS cross-currency bases within the sub-sample. More details on the quarter-end behavior of the forward CIP trade can be found in Section 3.4.

Figure A5: **Treasury repo outstanding and rate**



Notes: This figure plots the time series of amounts outstanding and spreads on Treasury repurchase agreements (repos) by primary dealers. "Tsy repo borrowing" refers to primary dealers' borrowing in the Treasury repo market, and "Tsy repo lending" refer primary dealers' lending in the Treasury repo market, as reported in the Primary Dealer Statistics published by the Federal Reserve Bank of New York. "Lending vs. borrowing spread" refers to the difference between DTCC's GCF's median Treasury repo rate and (1) Bank of New York Mellon's median Triparty Treasury repo rate after August 2012; (2) Federal Reserve Bank of New York's historical primary dealer average Treasury repo financing rate before August 2012. The repo spread measures the spread between primary dealers' lending rate and borrowing rate in the Treasury repo market. The shaded area marks the period between July 1, 2007 and July 1, 2010.

Table A1: **OIS and IBOR Conventions for Sample Currencies**

Panel A: OIS		
Currency	Indexed Rate	Day Count
AUD	Reserve Bank of Australia Interbank Overnight Cash Rate	ACT / 365
CAD	Canadian Overnight Repo Rate Average (CORRA)	ACT / 365
CHF	Tomorrow/Next Overnight Indexed Swaps (TOIS, ends in 2017)	ACT / 360
EUR	EMMI Euro Overnight Index Average (EONIA)	ACT / 360
GBP	Sterling Overnight Index Average (SONIA)	ACT / 365
JPY	Bank of Japan Estimate Unsecured Overnight Call Rate	ACT / 365
USD	US Federal Funds Effective Rate	ACT / 360
Panel B: IBOR		
Currency	Interbank Rate	Day Count
AUD	Australia Bank Bill Swap Rate (BBSW)	ACT / 365
CAD	Canada Bankers' Acceptances Rate	ACT / 365
CHF	ICE LIBOR CHF	ACT / 360
EUR	Euribor	ACT / 360
GBP	ICE LIBOR GBP	ACT / 365
JPY	ICE LIBOR JPY	ACT / 360
USD	ICE LIBOR USD	ACT / 360

Notes: This table reports the Overnight Index Swap and IBOR conventions for sample currencies. The Overnight Rate refers to the reference rate used to calculate the interest on the floating leg, against the expectation of which, the rate on the fixed leg is determined. The Day Count specifies how interests are calculated from the quoted annualized rate. For example, with a quoted annualized rate of 2%, a 32-day contract with a day count of ACT/360 would earn an interest of $(1 + 0.02 \times 32/360) - 1$.

Table A2: **Summary Statistics of Currency Pair Returns on IBOR 1M-forward 3M Forward CIP Trading Strategy**

	Mean			Sharpe Ratio			Post-GFC Metrics	
	Pre-GFC	GFC	Post-GFC	Pre-GFC	GFC	Post-GFC	Avg Basis	Int. Rate Diff.
AUD_JPY	4.65***	-11.58	15.44***	1.10***	-0.47	1.26***	36.48	2.43
	(1.49)	(9.34)	(3.12)	(0.33)	(0.37)	(0.42)		
AUD_EUR	1.62	-38.92***	6.07*	0.39	-1.75***	0.56*	35.78	2.38
	(1.35)	(10.96)	(3.12)	(0.32)	(0.32)	(0.33)		
AUD_CHF	5.17***	-21.01**	9.29***	1.20***	-0.89***	0.69**	32.51	2.88
	(1.53)	(9.15)	(3.47)	(0.38)	(0.33)	(0.32)		
AUD_CAD	-0.57	-9.24	-2.60	-0.10	-0.36	-0.27	30.57	1.21
	(2.30)	(6.79)	(2.92)	(0.42)	(0.24)	(0.26)		
USD_JPY	2.23**	5.44	8.21***	0.80**	0.19	0.77***	26.84	0.81
	(1.13)	(12.62)	(2.58)	(0.40)	(0.44)	(0.24)		
USD_EUR	-0.62	-21.04**	-1.17	-0.25	-0.87***	-0.11	26.14	0.75
	(0.54)	(10.07)	(3.09)	(0.22)	(0.30)	(0.29)		
USD_CHF	2.87***	-3.17	2.06	1.02***	-0.13	0.15	22.86	1.26
	(0.86)	(9.96)	(3.63)	(0.31)	(0.39)	(0.27)		
USD_CAD	-2.98**	8.18	-9.45***	-0.70**	0.43	-1.34***	20.93	-0.42
	(1.39)	(8.92)	(1.92)	(0.32)	(0.42)	(0.45)		
AUD_GBP	1.94	-31.65**	2.97	0.38	-1.28***	0.35	18.98	1.88
	(1.60)	(13.83)	(2.34)	(0.31)	(0.38)	(0.31)		
GBP_JPY	3.13	19.73	12.51***	0.65*	0.68*	1.38***	17.49	0.55
	(1.93)	(14.90)	(2.29)	(0.39)	(0.36)	(0.27)		

Standard errors in parentheses

This table reports the annual profits and annualized Sharpe ratios from the IBOR 1M-forward 3M forward CIP trading strategy for the ten currency pairs with the largest average Post-GFC spot 3M bases. All statistics are reported by period: Pre-GFC is 2003-01-01 to 2007-06-30, GFC is 2007-07-01 to 2010-06-30, and Post-GFC is 2010-07-01 to 2020-12-31. "Avg. Basis" is the average spot 3M IBOR cross-currency basis post-GFC, and "Int. Rate Diff." is the average spread between the 3M foreign IBOR rate and the US LIBOR rate post-GFC. Newey-West standard errors are reported in parentheses, where the bandwidth is chosen by the Newey and West (1994) selection procedure. *, **, and *** denote significance levels at 10%, 5%, and 1% confidence levels.

Table A3: **Summary Statistics of Portfolio Returns on OIS 1M-forward 1M Forward CIP Trading Strategy**

	Mean			Sharpe Ratio		
	Pre-GFC	GFC	Post-GFC	Pre-GFC	GFC	Post-GFC
Classic Carry (AUD-JPY)	1.88**	0.02	7.27***	1.06**	0.00	0.98**
	(0.73)	(3.24)	(1.70)	(0.45)	(0.26)	(0.41)
Dollar-Neutral Carry	0.56*	-5.36	5.09***	0.60*	-0.52***	1.12***
	(0.33)	(3.27)	(1.04)	(0.36)	(0.20)	(0.38)
Dynamic Top-Five Basis	0.93**	-3.43	4.92***	0.91**	-0.23	0.83**
	(0.40)	(5.61)	(1.35)	(0.39)	(0.31)	(0.38)
Static Top-Six Basis	0.83**	-3.90	4.68***	0.87**	-0.30	0.84**
	(0.38)	(4.90)	(1.29)	(0.42)	(0.29)	(0.37)
Simple Dollar	-0.42	1.70	0.69	-0.60	0.10	0.19
	(0.38)	(8.40)	(0.89)	(0.53)	(0.48)	(0.23)
Top-Six First PC	0.78	-4.58	6.05***	0.59	-0.27	0.82**
	(0.58)	(6.35)	(1.69)	(0.45)	(0.30)	(0.38)

Standard errors in parentheses

Notes: This table reports the annual profits and annualized Sharpe ratios from the OIS 1M-forward 1M forward CIP trading strategy. All statistics are reported by period: Pre-GFC is 2003-01-01 to 2007-06-30, GFC is 2007-07-01 to 2010-06-30, and Post-GFC is 2010-07-01 to 2020-12-31. The "Classic Carry" portfolio is the forward CIP trading strategy for the AUD-JPY pair. The "Dollar-Neutral Carry" portfolio longs the forward CIP trading strategy in AUD, CAD, and GBP and shorts the forward CIP trading strategy in JPY and EUR. The "Dynamic Top-Five Basis" portfolio has equal weight in the 5 currency pairs that exhibit the highest spot 3M basis, rebalanced monthly. The "Static Top Six Basis" portfolio has equal weights in the six non-CHF currency pairs with the largest average spot 3M basis post-GFC shown in Table 2. The "Simple Dollar" portfolio puts equal weights on the forward CIP trading strategy for all non-CHF sample currencies vis-à-vis the USD. The "Top-Six First PC" portfolio is the first principal component of the six non-CHF currency pair returns with the largest average spot 3M basis post-GFC shown in Table 2. Newey-West standard errors are reported in parentheses, where the bandwidth is chosen by the Newey and West (1994) selection procedure. *, **, and *** denote significance levels at 10%, 5%, and 1% confidence levels.

Table A4: **Summary Statistics of Portfolio Returns on OIS 3M-forward 3M Forward CIP Trading Strategy**

	Mean			Sharpe Ratio		
	Pre-GFC	GFC	Post-GFC	Pre-GFC	GFC	Post-GFC
Classic Carry (AUD-JPY)	0.72	0.50	11.74***	0.17	0.03	1.07***
	(1.03)	(3.97)	(2.29)	(0.26)	(0.26)	(0.27)
Dollar-Neutral Carry	-0.52	1.48	8.34***	-0.19	0.15	1.20***
	(0.98)	(2.71)	(1.48)	(0.31)	(0.30)	(0.30)
Dynamic Top-Five Basis	-0.59	-0.97	8.19***	-0.19	-0.06	0.98***
	(1.24)	(5.45)	(1.73)	(0.34)	(0.33)	(0.27)
Static Top-Six Basis	-0.73	-1.31	7.93***	-0.22	-0.09	0.98***
	(1.34)	(4.87)	(1.69)	(0.33)	(0.31)	(0.27)
Simple Dollar	1.17	7.31	1.22	0.34	0.30	0.22
	(1.47)	(9.29)	(1.13)	(0.33)	(0.35)	(0.20)
Top-Six First PC	-0.97	-1.69	10.84***	-0.22	-0.09	1.00***
	(1.82)	(6.38)	(2.26)	(0.34)	(0.31)	(0.28)

Standard errors in parentheses

Notes: This table reports the annual profits and annualized Sharpe ratios from the OIS 3M-forward 3M forward CIP trading strategy. Pre-GFC is 2003-01-01 to 2007-06-30, GFC is 2007-07-01 to 2010-06-30, and Post-GFC is 2010-07-01 to 2021-2-28 (the last trading day is 2020-11-30). The "Classic Carry" portfolio is the forward CIP trading strategy for the AUD-JPY pair. The "Dollar-Neutral Carry" portfolio longs the forward CIP trading strategy in AUD, CAD, and GBP and shorts the forward CIP trading strategy in JPY and EUR. The "Dynamic Top-Five Basis" portfolio has equal weight in the 5 currency pairs that exhibit the highest spot 3M basis, rebalanced monthly. The "Static Top Six Basis" portfolio has equal weights in the six non-CHF currency pairs with the largest average spot 3M basis post-GFC shown in Table 2. The "Simple Dollar" portfolio puts equal weights on the forward CIP trading strategy for all non-CHF sample currencies vis-à-vis the USD. The "Top-Six First PC" portfolio is the first principal component of the six non-CHF currency pair returns with the largest average spot 3M basis post-GFC shown in Table 2. Newey-West standard errors are reported in parentheses, where the bandwidth is chosen by the Newey and West (1994) selection procedure. *, **, and *** denote significance levels at 10%, 5%, and 1% confidence levels.

Table A5: **Summary Statistics of Portfolio Returns on IBOR 1M-forward 3M Forward CIP Trading Strategy**

	Mean			Sharpe Ratio		
	Pre-GFC	GFC	Post-GFC	Pre-GFC	GFC	Post-GFC
Classic Carry (AUD-JPY)	4.65***	-11.58	15.44***	1.10***	-0.47	1.26***
	(1.49)	(9.34)	(3.12)	(0.33)	(0.37)	(0.42)
Dollar-Neutral Carry	3.40***	-7.81	8.80***	1.08***	-0.51	1.07***
	(1.19)	(5.18)	(2.20)	(0.36)	(0.35)	(0.34)
Dynamic Top-Five Basis	3.79***	-20.35***	8.94***	1.39***	-1.04***	0.85***
	(0.95)	(7.59)	(2.75)	(0.33)	(0.25)	(0.32)
Static Top-Eight Basis	2.82***	-12.71**	6.94***	1.26***	-0.80***	0.83***
	(0.78)	(5.78)	(2.19)	(0.33)	(0.27)	(0.31)
Simple Dollar	-0.36	3.40	0.44	-0.18	0.16	0.06
	(0.71)	(8.82)	(2.05)	(0.37)	(0.40)	(0.26)
Top-Eight First PC	4.21***	-17.60**	9.63***	1.35***	-0.77***	0.78**
	(1.09)	(8.24)	(3.22)	(0.32)	(0.27)	(0.31)

Standard errors in parentheses

Notes: This table reports the annual profits and annualized Sharpe ratios from the IBOR 1M-forward 3M forward CIP trading strategy. Pre-GFC is 2003-01-01 to 2007-06-30, GFC is 2007-07-01 to 2010-06-30, and Post-GFC is 2010-07-01 to 2020-12-31. The "Classic Carry" portfolio is the forward CIP trading strategy for the AUD-JPY pair. The "Dollar-Neutral Carry" portfolio longs the forward CIP trading strategy in AUD and GBP (1/2 weight each) and shorts the forward CIP trading strategy in JPY, CHF, and EUR (1/3 weight each). The "Dynamic Top-Five Basis" portfolio has equal weight in the 5 non-CAD currency pairs that exhibit the highest spot 3M basis, rebalanced monthly. The "Static Top Eight Basis" portfolio has equal weights in the eight non-CAD currency pairs with the largest average spot 3M basis post-GFC shown in Table A2. The "Simple Dollar" portfolio puts equal weights on the forward CIP trading strategy for all non-CAD sample currencies vis-à-vis the USD. The "Top-Eight First PC" portfolio is the first principal component of the eight non-CAD currency pair returns with the largest average spot 3M basis post-GFC shown in Table A2. Newey-West standard errors are reported in parentheses, where the bandwidth is chosen by the Newey and West (1994) selection procedure. *, **, and *** denote significance levels at 10%, 5%, and 1% confidence levels.

Table A6: **Summary Statistics of Portfolio Returns on IBOR 3M-forward 3M Forward CIP Trading Strategy**

	Mean			Sharpe Ratio		
	Pre-GFC	GFC	Post-GFC	Pre-GFC	GFC	Post-GFC
Classic Carry (AUD-JPY)	1.66**	-1.33	10.89***	0.55**	-0.10	1.21***
	(0.67)	(3.36)	(1.80)	(0.28)	(0.23)	(0.32)
Dollar-Neutral Carry	1.32***	-0.46	6.36***	0.69***	-0.05	0.99***
	(0.37)	(2.11)	(1.35)	(0.23)	(0.24)	(0.28)
Dynamic Top-Five Basis	1.17**	-7.25*	5.90***	0.53	-0.58**	0.76***
	(0.57)	(4.18)	(1.62)	(0.36)	(0.26)	(0.27)
Static Top-Eight Basis	0.92**	-4.45	4.97***	0.53	-0.46*	0.76***
	(0.43)	(2.90)	(1.35)	(0.35)	(0.24)	(0.26)
Simple Dollar	0.35	4.58	-0.23	0.26	0.37	-0.04
	(0.32)	(3.96)	(1.12)	(0.20)	(0.32)	(0.20)
Top-Eight First PC	1.25**	-7.15*	6.12***	0.53	-0.52**	0.68***
	(0.61)	(4.26)	(1.89)	(0.35)	(0.25)	(0.26)

Standard errors in parentheses

Notes: This table reports the annual profits and annualized Sharpe ratios from the IBOR 3M-forward 3M forward CIP trading strategy. All statistics are reported by period: Pre-GFC is 2003-01-01 to 2007-06-30, GFC is 2007-07-01 to 2010-06-30, and Post-GFC is 2010-07-01 to 2021-2-28 (the last trading day is 2020-11-30). The "Classic Carry" portfolio is the forward CIP trading strategy for the AUD-JPY pair. The "Dollar-Neutral Carry" portfolio longs the forward CIP trading strategy in AUD and GBP (1/2 weight each) and shorts the forward CIP trading strategy in JPY, CHF, and EUR (1/3 weight each). The "Dynamic Top-Five Basis" portfolio has equal weight in the 5 non-CAD currency pairs that exhibit the highest spot 3M basis, rebalanced monthly. The "Static Top Eight Basis" portfolio has equal weights in the eight non-CAD currency pairs with the largest average spot 3M basis post-GFC shown in Table A2. The "Simple Dollar" portfolio puts equal weights on the forward CIP trading strategy for all non-CAD sample currencies vis-à-vis the USD. The "Top-Eight First PC" portfolio is the first principal component of the eight non-CAD currency pair returns with the largest average spot 3M basis post-GFC shown in Table A2. Newey-West standard errors are reported in parentheses, where the bandwidth is chosen by the Newey and West (1994) selection procedure. *, **, and *** denote significance levels at 10%, 5%, and 1% confidence levels.

Table A7: **Summary Statistics of Non-Overlapping Monthly Portfolio Returns on OIS 1M-forward 3M Forward CIP Trading Strategy**

	Mean			Sharpe Ratio		
	Pre-GFC	GFC	Post-GFC	Pre-GFC	GFC	Post-GFC
Classic Carry (AUD-JPY)	1.41	2.64	18.12***	0.39	0.10	1.50***
	(1.81)	(15.27)	(3.72)	(0.49)	(0.58)	(0.31)
Dollar-Neutral Carry	1.78	-7.76	12.62***	0.68	-0.30	1.66***
	(1.35)	(14.72)	(2.35)	(0.48)	(0.49)	(0.30)
Dynamic Top-Five Basis	1.87	-6.35	11.91***	0.81	-0.17	1.28***
	(1.20)	(21.31)	(2.87)	(0.49)	(0.52)	(0.31)
Static Top-Six Basis	2.02*	-7.73	11.15***	0.94*	-0.22	1.23***
	(1.11)	(19.68)	(2.80)	(0.48)	(0.51)	(0.31)
Simple Dollar	-0.60	10.00	3.39*	-0.30	0.24	0.54*
	(1.03)	(23.83)	(1.93)	(0.52)	(0.51)	(0.29)
Top-Six First PC	2.55*	-9.02	14.33***	0.93*	-0.20	1.22***
	(1.41)	(25.13)	(3.63)	(0.49)	(0.52)	(0.32)

Standard errors in parentheses

Notes: This table reports the annual profits and annualized Sharpe ratios from the OIS 1M-forward 3M forward CIP trading strategy based on non-overlapping month-end daily observations. All statistics are reported by period: Pre-GFC is 2003-01-01 to 2007-06-30, GFC is 2007-07-01 to 2010-06-30, and Post-GFC is 2010-07-01 to 2020-12-31. The "Classic Carry" portfolio is the forward CIP trading strategy for the AUD-JPY pair. The "Dollar-Neutral Carry" portfolio longs the forward CIP trading strategy in AUD, CAD, and GBP and shorts the forward CIP trading strategy in JPY and EUR. The "Dynamic Top-Five Basis" portfolio has equal weight in the 5 currency pairs that exhibit the highest spot 3M basis, rebalanced monthly. The "Static Top Six Basis" portfolio has equal weights in the six non-CHF currency pairs with the largest average spot 3M basis post-GFC shown in Table 2. The "Simple Dollar" portfolio puts equal weights on the forward CIP trading strategy for all non-CHF sample currencies vis-à-vis the USD. The "Top-Six First PC" portfolio is the first principal component of the six non-CHF currency pair returns with the largest average spot 3M basis post-GFC shown in Table 2. Newey-West standard errors are reported in parentheses, where the bandwidth is chosen by the Newey and West (1994) selection procedure. *, **, and *** denote significance levels at 10%, 5%, and 1% confidence levels.

Table A8: **Pre/Post SLR Statistics of Portfolio Returns on OIS 1M-forward 3M Forward CIP Trading Strategy**

	Mean			Sharpe Ratio		
	Pre 2015	Post 2015	Overall	Pre 2015	Post 2015	Overall
Classic Carry (AUD-JPY)	12.84***	18.83***	16.25***	1.31**	1.17**	1.18***
	(4.74)	(5.12)	(3.57)	(0.53)	(0.50)	(0.39)
Dollar-Neutral Carry	9.63***	12.33***	11.16***	1.32**	1.26**	1.27***
	(3.54)	(2.97)	(2.29)	(0.52)	(0.53)	(0.40)
Dynamic Top-Five Basis	10.39***	11.94***	11.27***	1.39***	0.92*	1.03***
	(3.54)	(4.12)	(2.80)	(0.51)	(0.48)	(0.39)
Static Top-Six Basis	9.61***	11.44***	10.65***	1.29**	0.92*	1.00**
	(3.59)	(3.97)	(2.74)	(0.51)	(0.48)	(0.39)
Simple Dollar	-1.00	3.24	1.41	-0.31	0.36	0.20
	(1.25)	(3.14)	(1.88)	(0.37)	(0.32)	(0.25)
Top-Six First PC	12.39***	14.99***	13.87***	1.31**	0.92*	1.00**
	(4.57)	(5.19)	(3.55)	(0.51)	(0.48)	(0.39)

Standard errors in parentheses

Notes:*Notes*: This table reports the annual profits and annualized Sharpe ratios from the OIS 1M-forward 3M forward CIP trading strategy by sub-samples. All statistics are reported by period: Pre-2015 is 2003-01-01 to 2014-12-31, Post-2015 is 2015-1-1 to 2020-12-31, and the overall is the full sample period. The "Classic Carry" portfolio is the forward CIP trading strategy for the AUD-JPY pair. The "Dollar-Neutral Carry" portfolio longs the forward CIP trading strategy in AUD, CAD, and GBP and shorts the forward CIP trading strategy in JPY and EUR. The "Dynamic Top-Five Basis" portfolio has equal weight in the 5 currency pairs that exhibit the highest spot 3M basis, rebalanced monthly. The "Static Top Six Basis" portfolio has equal weights in the six non-CHF currency pairs with the largest average spot 3M basis post-GFC shown in Table 2. The "Simple Dollar" portfolio puts equal weights on the forward CIP trading strategy for all non-CHF sample currencies vis-à-vis the USD. The "Top-Six First PC" portfolio is the first principal component of the six non-CHF currency pair returns with the largest average spot 3M basis post-GFC shown in Table 2. Newey-West standard errors are reported in parentheses, where the bandwidth is chosen by the Newey and West (1994) selection procedure. *, **, and *** denote significance levels at 10%, 5%, and 1% confidence levels.

Table A9: **Bayesian Posterior Prob of SDF Models with AUD-JPY Forward CIP Return**

Factor Space	Model	Probability	Subtotal
{Market, Int. Equity, Fwd. CIP Ret.}	Market	0.005	
	Int. Equity	0.000	
	Market + Int. Equity	0.003	0.007
	Fwd. CIP Ret.	0.471	
	Market + Fwd. CIP Ret.	0.281	
	Int.Equity + Fwd. CIP Ret.	0.061	
	Market + Int. Equity + Fwd. CIP Ret.	0.179	0.993
{HKM Factor, Market, Fwd. CIP Ret.}	HKM Factor	0.000	
	HKM Factor + Market	0.008	0.008
	HKM Factor + Fwd. CIP Ret.	0.056	
	HKM Factor + Market + Fwd. CIP Ret.	0.936	0.992
{AEM Factor, Market, Fwd. CIP Ret.}	AEM Factor	0.074	
	AEM Factor + Market	0.068	0.142
	AEM Factor + Fwd. CIP Ret.	0.713	
	AEM Factor + Market + Fwd. CIP Ret.	0.145	0.858

Notes: In this table, we report posterior probabilities for factor models that do and do not include the AUD-JPY forward CIP return, using the method of Chib et al. (2020) (see Internet Appendix J for details).

Table A10: **Forward CIP Trading Strategy Return Predictability**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Basis Spread 1M-3M		0.496***	0.232	0.265	0.303	0.500***	0.237	0.300
		(0.169)	(0.234)	(0.207)	(0.198)	(0.186)	(0.259)	(0.225)
Spot Basis 3M				0.0973**	0.123**			0.0950**
				(0.0384)	(0.0608)			(0.0384)
Constant	0.0622***		0.0502**		-0.0189		0.0500**	
	(0.0125)		(0.0206)		(0.0237)		(0.0211)	
RMSE	0.140	0.145	0.139	0.135	0.136	0.145	0.138	0.134
R^2						0.104	0.183	0.226
1st Stage F						181.5	103.3	140.1
Instrument Lag (bus. days)						1	1	1
Observations	126	126	126	126	126	126	126	126

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table reports return predictability regressions for the classic carry (AUD-JPY) forward CIP trading strategy. The outcome variable in all columns is the one-month return of the three-month OIS forward CIP trading strategy. All data is monthly and post-GFC (2010-07 to 2020-12). Basis Spread 1M-3M is the spread between the 1-month forward three-month AUD-JPY basis and the spot three-month AUD-JPY basis. Spot Basis 3m is the spot three month AUD-JPY basis. RMSE is the root-mean-squared error, R^2 is the un-centered R^2, 1st Stage F is the F-statistic from the first stage for the IV regressions (see Stock and Yogo (2005)), and Instrument Lag is the number of business days the spread variable is lagged in the IV regression. Units are in percentage points.

Table A11: **Forward CIP Trading Strategy Return Predictability, Pre-2020**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Basis Spread 1M-3M		0.608***	0.400***	0.413***	0.437***	0.652***	0.465**	0.494***
		(0.135)	(0.152)	(0.137)	(0.146)	(0.153)	(0.186)	(0.166)
Spot Basis 3m				0.0719***	0.0892**			0.0661***
				(0.0245)	(0.0445)			(0.0251)
Constant	0.0593***		0.0379***		-0.0128		0.0344**	
	(0.0113)		(0.0136)		(0.0221)		(0.0146)	
RMSE	0.121	0.120	0.116	0.114	0.115	0.120	0.116	0.113
R^2						0.200	0.256	0.284
1st Stage F						143.5	81.99	110.6
Instrument Lag (bus. days)						1	1	1
Observations	114	114	114	114	114	114	114	114

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table reports return predictability regressions for the classic carry (AUD-JPY) forward CIP trading strategy. The outcome variable in all columns is the one-month return of the three-month OIS forward CIP trading strategy. All data is monthly, post-GFC, and pre-2020 (2010-07 to 2019-12). Basis Spread 1M-3M is the spread between the 1-month forward three-month AUD-JPY basis and the spot three-month AUD-JPY basis. Spot Basis 3m is the spot three month AUD-JPY basis. RMSE is the root-mean-squared error, R^2 is the un-centered R^2, 1st Stage F is the F-statistic from the first stage for the IV regressions (see Stock and Yogo (2005)), and Instrument Lag is the number of business days the spread variable is lagged in the IV regression. Units are in percentage points.

Table A12: **Returns on Quarter- and Year-end Crossing Forward CIP Trading Strategy Returns**

	OIS 1M-Forward 1M Returns							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
QE Cross: Interest Tenor		−0.045		−0.052				−0.076
		(0.050)		(0.049)				(0.064)
QE Cross: Forward Horizon			0.012	−0.014				−0.017
			(0.029)	(0.024)				(0.028)
YE Cross: Interest Tenor					0.050		0.053	0.100
					(0.062)		(0.062)	(0.086)
YE Cross: Forward Horizon						0.018	0.023	0.012
						(0.043)	(0.038)	(0.043)
Constant	0.073***	0.088***	0.069***	0.095***	0.068***	0.071***	0.066***	0.095***
	(0.021)	(0.015)	(0.027)	(0.019)	(0.022)	(0.022)	(0.023)	(0.018)
F-stat				0.606			0.451	0.453
Observations	2,552	2,552	2,552	2,552	2,552	2,552	2,552	2,552
R^2	0.000	0.007	0.0005	0.007	0.003	0.0004	0.004	0.017
Residual Std. Error	0.256	0.255	0.256	0.255	0.255	0.256	0.255	0.254

Standard errors are in parentheses

Notes: This table reports regressions of the classic-carry (AUD-JPY) forward CIP trading strategy return on indicators of quarter-ends and year-ends. The outcome variable in all columns is the one-month return of the one-month forward CIP trading strtegy. All data are daily and post-GFC (2010-07-01 to 2020-12-31). Quarter-end (QE) and year-end (YE) dummies indicate whether the 1M OIS interest-tenor or the 1M forward horizon crosses QE or YE. Newey-West standard errors are reported in parentheses, where the bandwidth is chosen by the Newey-West (1994) selection procedure. *, **, and *** denote significance levels at 10%, 5%, and 1% confidence levels.

Table A13: **Transaction Costs of USD-JPY Forward CIP Trade (Basis Points)**

(1) 1M-Forward 3M Forward		(2) 3M-Forward 3M Forward	
(A) Initiate forward CIP position			
Long 1Mv4M JPY OIS	0.53	Long 3M6M JPY OIS	0.37
Short 1Mv4M USD OIS	0.15	Short 3M6M USD OIS	0.16
Long USD-JPY 1Mv4M	0.74	Long USD-JPY 3M6M	0.72
(B) Unwind forward at the spot CIP			
Sell 3M JPY OIS	0.20	Sell 3M JPY OIS	0.20
Long 3M USD OIS	0.12	Long 3M USD OIS	0.12
Short USD-JPY 3M	0.22	Short USD-JPY 3M	0.22
(C) Estimated transaction costs vs profits			
Total cost per trade	1.96	Total cost per trade	1.78
Number of trades per year	12	Number of trades per year	4
Annual costs	23.49	Annual costs	7.10
Annual profits post-GFC	8.66	Annual profits post-GFC	6.85

Notes: This table shows the estimated transaction costs on USD-JPY forward CIP trade for the one-month horizon in Column 1 and three-month horizon in Column 2. All transaction costs in Panel A and Panel B are equal to the mean half bid-ask spreads on the corresponding instrument from Bloomberg. The sample period is post-GFC from 2010-07-01 to 2020-12-31.

Table A14: **Cross-sectional Asset Pricing Tests, Pre-2020 Data**

	(1) US	(2) Sov	(3) FX	(4) Opt	(5) FwdArb	(6) CDS	(7) FF6	(8) Comm	(9) 1-8
Int. Equity	0.706	1.945	2.330	1.081	0.247	2.293	-1.408	0.182	0.860
	(0.721)	(1.209)	(0.731)	(0.967)	(1.171)	(1.009)	(2.828)	(0.805)	(0.447)
Fwd. CIP Ret. PC1	-0.192	-0.0677	-0.0254	-0.113	-0.0580	-0.0331	0.182	-0.0197	-0.0620
	(0.113)	(0.0678)	(0.0454)	(0.0444)	(0.0125)	(0.141)	(0.227)	(0.0526)	(0.0133)
Intercepts	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MAPE (%/mo.)	0.029	0.034	0.068	0.038	0.008	0.016	0.063	0.201	
H1 p-value	0.461	0.431	0.046	0.343	0.217	0.083	0.510	0.741	0.243
KZ p-value	0.083	0.230	0.055	0.016	0.000	0.819	0.836	0.493	0.000
N (assets)	11	6	11	12	13	5	6	6	70
N (beta, mos.)	114	114	114	114	114	114	114	114	
N (mean, mos.)	376	300	434	288	114	186	1121	347	

Standard errors in parentheses

Notes: This table reports estimates for the price of risk (λ in Equation (12)) from the various asset classes described in Internet Appendix Section K. The data sample ends in December 2020. "Fwd. CIP Ret. PC1" is the return of the first principal component of the 1M-fwd 3M forward CIP trading strategies described in the text and "Int. Equity" is the intermediary equity return of He et al. (2017). Intercepts indicates an intercept is used for each asset class (one intercept per column, with eight in (9), which pools the first eight asset classes). MAPE is mean absolute pricing error of monthly returns. H1 p-value tests whether the price of the Fwd. CIP Ret. PC1 and Int. Equity risks are equal to the mean excess returns of those trading strategies. KZ p-value is the p-value of the Kleibergen and Zhan (2020) test rejecting reduced rank for the betas of the test assets. Standard errors are computed using GMM with the Newey-West kernel and a twelve-month bandwidth. Units are in percentage points.

Table A15: **Cross-sectional Asset Pricing Tests, HKM 2-Factor Non-Tradable**

	(1) US	(2) Sov	(3) FX	(4) Opt	(5) FwdArb	(6) CDS	(7) FF6	(8) Comm	(9) 1-8
Market	1.180	-0.103	2.184	1.704	1.472	1.021	0.929	0.987	1.096
	(0.779)	(0.773)	(0.868)	(0.985)	(3.184)	(0.908)	(0.555)	(1.083)	(0.535)
HKM Factor	-1.717	1.966	4.743	1.674	3.914	2.255	2.511	-0.756	0.547
	(1.378)	(2.546)	(2.266)	(5.864)	(11.21)	(3.246)	(1.250)	(1.009)	(1.808)
Intercepts	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MAPE (%/mo.)	0.031	0.041	0.055	0.087	0.017	0.042	0.125	0.143	
H1 p-value	0.501	0.329	0.082	0.298	0.803	0.699	0.615	0.776	0.420
KZ p-value	0.000	0.305	0.663	0.278	0.345	0.025	0.000	0.007	0.000
N (assets)	11	6	11	12	13	5	6	6	70
N (beta, mos.)	388	312	446	300	126	198	612	359	
N (mean, mos.)	388	312	446	300	126	198	1133	359	

Standard errors in parentheses

Notes: This table reports estimates for the price of risk (λ in Equation (12)) from the various asset classes described in Internet Appendix Section K. "Market" is the CRSP market return, and "HKM factor" is the intermediary capital ratio innovation of He et al. (2017). Intercepts indicates an intercept is used for each asset class (one intercept per column, with eight in (9), which pools the first eight asset classes). MAPE is mean absolute pricing error of monthly returns. H1 p-value tests whether the price of the Market risk is equal to its mean excess return. KZ p-value is the p-value of the Kleibergen and Zhan (2020) test rejecting reduced rank for the betas of the test assets. Standard errors are computed using GMM with the Newey-West kernel and a twelve-month bandwidth. Units are in percentage points.

Table A16: **Cross-sectional Asset Pricing Tests, HKM 2-Factor Tradable**

	(1) US	(2) Sov	(3) FX	(4) Opt	(5) FwdArb	(6) CDS	(7) FF6	(8) Comm	(9) 1-8
Market	1.318	-0.213	1.261	1.591	2.349	0.455	0.878	1.264	0.980
	(0.874)	(1.204)	(1.013)	(0.789)	(2.675)	(1.416)	(0.543)	(1.381)	(0.439)
Int. Equity	-1.757	1.942	4.641	2.494	4.968	3.863	2.096	-0.248	1.050
	(1.336)	(3.271)	(2.229)	(7.170)	(4.386)	(3.350)	(1.067)	(1.070)	(1.149)
Intercepts	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MAPE (%/mo.)	0.036	0.049	0.049	0.083	0.015	0.034	0.127	0.153	
H1 p-value	0.212	0.675	0.049	0.297	0.585	0.318	0.087	0.516	0.704
KZ p-value	0.000	0.782	0.359	0.550	0.316	0.024	0.000	0.057	0.000
N (assets)	11	6	11	12	13	5	6	6	70
N (beta, mos.)	388	312	446	300	126	198	612	359	
N (mean, mos.)	388	312	446	300	126	198	1133	359	

Standard errors in parentheses

Notes: This table reports estimates for the price of risk (λ in Equation (12)) from the various asset classes described in Internet Appendix Section K. "Market" is the CRSP market return, and "Int. Equity" is the intermediary equity return of He et al. (2017). Intercepts indicates an intercept is used for each asset class (one intercept per column, with eight in (9), which pools the first eight asset classes). MAPE is mean absolute pricing error of monthly returns. H1 p-value tests whether the price of the Market and Int. Equity risks are equal to the mean excess returns of those trading strategies. KZ p-value is the p-value of the Kleibergen and Zhan (2020) test rejecting reduced rank for the betas of the test assets. Standard errors are computed using GMM with the Newey-West kernel and a twelve-month bandwidth. Units are in percentage points.

Table A17: **Cross-sectional Asset Pricing Tests, AEM 2-Factor (Quarterly)**

	(1) US	(2) Sov	(3) FX	(4) Opt	(5) CDS	(6) FF6	(7) Comm	(8) 1-7
Market	0.657	1.310	6.845	4.898	3.444	1.290	0.778	2.122
	(0.946)	(1.108)	(1.747)	(2.138)	(1.217)	(1.292)	(2.389)	(1.037)
AEM Lev. Change	-0.391	1.840	-1.074	-5.247	-0.212	7.302	0.473	0.115
	(5.128)	(3.818)	(3.583)	(9.364)	(1.933)	(2.808)	(2.421)	(1.804)
Intercepts	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MAPE (%/qtr.)	0.237	0.127	0.182	0.280	0.064	0.141	0.619	
H1 p-value	0.120	0.443	0.009	0.196	0.293	0.478	0.551	0.955
KZ p-value	0.001	0.206	0.097	0.001	0.050	0.003	0.025	0.115
N (assets)	11	6	11	12	5	6	6	57
N (beta, qtrs.)	129	104	148	100	66	212	119	
N (mean, qtrs.)	129	104	148	100	66	377	119	

Standard errors in parentheses

Notes: This table reports estimates for the price of risk (λ in Equation (12)) from the various asset classes described in Internet Appendix Section K. "Market" is the CRSP market return, and "AEM Lev. Change" is the seasonally-adjusted change in dealer leverage of Adrian et al. (2014). Intercepts indicates an intercept is used for each asset class (one intercept per column, with seven in (9), which pools the first seven asset classes). This table omits the forward CIP asset class due to data limitations. MAPE is mean absolute pricing error of quarterly returns. H1 p-value tests whether the price of the Market risk is equal to the mean excess returns of that trading strategies. KZ p-value is the p-value of the Kleibergen and Zhan (2020) test rejecting reduced rank for the betas of the test assets. Standard errors are computed using GMM with the Newey-West kernel and a four-quarter bandwidth. Units are in percentage points.

Table A18: **Cross-sectional Asset Pricing Tests, Market + Fwd. CIP Return**

	(1) US	(2) Sov	(3) FX	(4) Opt	(5) FwdArb	(6) CDS	(7) FF6	(8) Comm	(9) 1-8
Market	-0.190	0.473	1.685	0.553	-3.703	0.917	0.801	0.667	0.378
	(0.295)	(0.582)	(0.494)	(0.425)	(2.615)	(0.577)	(0.389)	(0.913)	(0.350)
Fwd. CIP Ret. PC1	-0.0656	-0.0455	-0.0708	-0.0703	-0.0393	-0.101	-0.0452	-0.210	-0.0485
	(0.0388)	(0.0564)	(0.0440)	(0.0391)	(0.0129)	(0.0953)	(0.0814)	(0.298)	(0.0193)
Intercepts	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MAPE (%/mo.)	0.056	0.051	0.062	0.057	0.010	0.006	0.101	0.073	
H1 p-value	0.017	0.934	0.130	0.866	0.161	0.541	0.944	0.830	0.664
KZ p-value	0.000	0.432	0.110	0.002	0.030	0.258	0.044	0.957	0.000
N (assets)	11	6	11	12	13	5	6	6	70
N (beta, mos.)	126	126	126	126	126	126	126	126	
N (mean, mos.)	388	312	446	300	126	198	1133	359	

Standard errors in parentheses

Notes: This table reports estimates for the price of risk (λ in Equation (12)) from the various asset classes described in Internet Appendix Section K. "Fwd. CIP Ret. PC1" is the return on the first principal component of the 1M-fwd 3M forward CIP trading strategy described in the text and "Market" is the CRSP market return. Intercepts indicates an intercept is used for each asset class (one intercept per column, with eight in (9), which pools the first eight asset classes). MAPE is mean absolute pricing error of monthly returns. H1 p-value tests whether the price of the Fwd. CIP Ret. PC1 and Market risks are equal to the mean excess returns of those trading strategies. KZ p-value is the p-value of the Kleibergen and Zhan (2020) test rejecting reduced rank for the betas of the test assets. Standard errors are computed using GMM with the Newey-West kernel and a twelve-month bandwidth. Units are in percentage points.

Table A19: **Cross-sectional Asset Pricing Tests, 3-Factor**

	(1) US	(2) Sov	(3) FX	(4) Opt	(5) FwdArb	(6) CDS	(7) FF6	(8) Comm	(9) 1-8
Market	1.211	0.193	1.403	1.421	-3.649	0.907	0.395	0.693	0.448
	(0.677)	(0.462)	(0.495)	(1.109)	(2.282)	(0.920)	(0.790)	(0.760)	(0.453)
Int. Equity	-0.845	1.419	2.997	-3.821	-1.799	1.324	0.977	0.732	0.426
	(0.523)	(1.763)	(1.092)	(3.220)	(2.159)	(2.159)	(0.627)	(1.617)	(0.500)
Fwd. CIP Ret. PC1	0.00296	-0.00990	-0.0588	-0.149	-0.0469	-0.0982	0.0293	-0.182	-0.0479
	(0.0220)	(0.0638)	(0.0402)	(0.0736)	(0.0132)	(0.0718)	(0.152)	(0.262)	(0.0191)
Intercepts	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MAPE (%/mo.)	0.017	0.022	0.052	0.040	0.010	0.006	0.098	0.010	
H1 p-value	0.005	0.593	0.087	0.536	0.046	0.549	0.366	0.944	0.941
KZ p-value	0.002	0.387	0.462	0.437	0.381	0.250	0.040	0.886	0.000
N (assets)	11	6	11	12	13	5	6	6	70
N (beta, mos.)	126	126	126	126	126	126	126	126	
N (mean, mos.)	388	312	446	300	126	198	1133	359	

Standard errors in parentheses

Notes: This table reports estimates for the price of risk (λ in Equation (12)) from the various asset classes described in Internet Appendix Section K. “Fwd. CIP Ret. PC1” is the return on the first principal component of the 1M-fwd 3M forward CIP trading strategy described in the text, “Market” is the CRSP market return, and “Int. Equity” is the intermediary equity return of He et al. (2017). Intercepts indicates an intercept is used for each asset class (one intercept per column, with eight in (9), which pools the first eight asset classes). MAPE is mean absolute pricing error of monthly returns. H1 p-value tests whether the price of the Fwd. CIP Ret. PC1, Market, and Int. Equity risks are equal to the mean excess returns of those trading strategies. KZ p-value is the p-value of the Kleibergen and Zhan (2020) test rejecting reduced rank for the betas of the test assets. Standard errors are computed using GMM with the Newey-West kernel and a twelve-month bandwidth. Units are in percentage points.

Table A20: **Cross-sectional Asset Pricing Tests, HKM 1-Factor**

	(1) US	(2) Sov	(3) FX	(4) Opt	(5) FwdArb	(6) CDS	(7) FF6	(8) Comm	(9) 1-8
Int. Equity	0.497	0.853	3.686	2.854	4.564	2.026	1.415	0.206	1.484
	(0.659)	(0.776)	(1.136)	(1.414)	(5.373)	(0.797)	(1.118)	(1.019)	(0.707)
Intercepts	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MAPE (%/mo.)	0.077	0.050	0.058	0.082	0.016	0.041	0.134	0.215	
H1 p-value	0.859	0.712	0.004	0.088	0.459	0.039	0.455	0.686	0.141
KZ p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
N (assets)	11	6	11	12	13	5	6	6	70
N (beta, mos.)	388	312	446	300	126	198	612	359	
N (mean, mos.)	388	312	446	300	126	198	1133	359	

Standard errors in parentheses

Notes: This table reports estimates for the price of risk (λ in Equation (12)) from the various asset classes described in Internet Appendix Section K. "Int. Equity" is the intermediary equity return of He et al. (2017). Intercepts indicates an intercept is used for each asset class (one intercept per column, with eight in (9), which pools the first eight asset classes). MAPE is mean absolute pricing error of monthly returns. H1 p-value tests whether the price of the Int. Equity risk is equal to its mean excess return. KZ p-value is the p-value of the Kleibergen and Zhan (2020) test rejecting reduced rank for the betas of the test assets. Standard errors are computed using GMM with the Newey-West kernel and a twelve-month bandwidth. Units are in percentage points.

Table A21: **Cross-sectional Asset Pricing Tests, 3 Factor Non-Tradable**

	(1) US	(2) Sov	(3) FX	(4) Opt	(5) FwdArb	(6) CDS	(7) FF6	(8) Comm	(9) 1-8
Market	1.419	0.177	1.593	1.489	-3.915	0.733	0.320	0.748	0.726
	(0.809)	(0.448)	(0.512)	(1.079)	(2.246)	(1.870)	(0.797)	(0.774)	(0.339)
HKM Factor	-1.400	1.116	3.440	-2.985	-3.407	2.144	0.920	1.035	0.0443
	(0.769)	(1.244)	(1.817)	(3.266)	(6.056)	(4.592)	(0.859)	(2.396)	(0.616)
Fwd. CIP Ret. PC1	-0.00628	-0.0215	-0.0701	-0.140	-0.0396	-0.0940	0.0380	-0.175	-0.0477
	(0.0254)	(0.0561)	(0.0413)	(0.0766)	(0.0151)	(0.0716)	(0.136)	(0.254)	(0.0190)
Intercepts	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MAPE (%/mo.)	0.010	0.025	0.050	0.025	0.010	0.005	0.097	0.011	
H1 p-value	0.235	0.431	0.179	0.486	0.083	0.757	0.812	0.886	0.980
KZ p-value	0.008	0.312	0.245	0.672	0.281	0.476	0.060	0.890	0.000
N (assets)	11	6	11	12	13	5	6	6	70
N (beta, mos.)	126	126	126	126	126	126	126	126	
N (mean, mos.)	388	312	446	300	126	198	1133	359	

Standard errors in parentheses

Notes: This table reports estimates for the price of risk (λ in Equation (12)) from the various asset classes described in Internet Appendix Section K. "Fwd. CIP Ret. PC1" is the return of the first principal component of the 1M-fwd 3M forward CIP trading strategies described in the text, "Market" is the CRSP market return, and "HKM Factor" is the intermediary capital ratio innovation of He et al. (2017). Intercepts indicates an intercept is used for each asset class (one intercept per column, with eight in (9), which pools the first eight asset classes). MAPE is mean absolute pricing error of monthly returns. H1 p-value tests whether the price of the Fwd. CIP Ret. PC1 and Market risks are equal to the mean excess returns of those trading strategies. KZ p-value is the p-value of the Kleibergen and Zhan (2020) test rejecting reduced rank for the betas of the test assets. Standard errors are computed using GMM with the Newey-West kernel and a twelve-month bandwidth. Units are in percentage points.

Table A22: **Cross-sectional Asset Pricing Tests, with Risk-Free Rate Adjustment**

	(1) US	(2) Sov	(3) FX	(4) Opt	(5) FwdArb	(6) CDS	(7) FF6	(8) Comm	(9) 1-8
Int. Equity	-0.307	0.697	2.765	0.387	-1.346	1.252	0.976	0.356	0.456
	(0.419)	(1.101)	(0.784)	(0.816)	(8.069)	(1.314)	(0.673)	(1.371)	(0.554)
Fwd. CIP Ret. PC1	-0.0576	-0.0361	-0.0517	-0.0775	-0.0399	-0.0853	0.0395	-0.152	-0.0476
	(0.0341)	(0.0623)	(0.0409)	(0.0415)	(0.0320)	(0.0823)	(0.150)	(0.132)	(0.0207)
Intercepts	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MAPE (%/mo.)	0.045	0.044	0.054	0.057	0.014	0.008	0.095	0.067	
H1 p-value	0.059	0.976	0.014	0.812	0.922	0.320	0.233	0.623	0.957
KZ p-value	0.000	0.545	0.217	0.016	0.001	0.069	0.077	0.864	0.000
N (assets)	11	6	11	12	13	5	6	6	70
N (beta, mos.)	126	126	126	126	126	126	126	126	
N (mean, mos.)	388	312	446	300	126	198	1133	359	

Standard errors in parentheses

Notes: This table reports estimates for the price of risk (λ in Equation (12)) from the various asset classes described in Internet Appendix Section K. Betas are estimated from a modified version of (13), $R^i_{t+1} - R^f_t = \mu_i + \beta^i_w(R^w_{t+1} - R^f_t) + \beta^i_x r^{|x|}_{t+1} + \beta^i_s|x_t| + \epsilon^i_{t+1}$, where $|x_t|$ is the AUD-JPY spot 3M basis. "Fwd. CIP Ret. PC1" is the return of the first principal component of the 1M-fwd 3M forward CIP trading strategies described in the text and "Int. Equity" is the intermediary equity return of He et al. (2017). Intercepts indicates an intercept is used for each asset class (one intercept per column, with eight in (9), which pools the first eight asset classes). MAPE is mean absolute pricing error of monthly returns. H1 p-value tests whether the price of the Fwd. CIP Ret. PC1 and Int. Equity risks are equal to the mean excess returns of those trading strategies. KZ p-value is the p-value of the Kleibergen and Zhan (2020) test rejecting reduced rank for the betas of the test assets. Standard errors are computed using GMM with the Newey-West kernel and a twelve-month bandwidth. Units are in percentage points.

Table A23: **Cross-sectional Asset Pricing Tests, AUD-JPY**

	(1) US	(2) Sov	(3) FX	(4) Opt	(5) FwdArb	(6) CDS	(7) FF6	(8) Comm	(9) 1-8
Int. Equity	-0.293	0.775	2.685	0.682	-1.838	1.545	1.028	0.334	0.491
	(0.415)	(1.032)	(0.816)	(0.766)	(7.974)	(0.926)	(0.491)	(1.169)	(0.560)
Neg. Fwd CIP Ret.	-0.0653	-0.0332	-0.0450	-0.0915	-0.0491	-0.0744	0.0116	-0.114	-0.0542
	(0.0389)	(0.0792)	(0.0376)	(0.0480)	(0.0201)	(0.0725)	(0.174)	(0.0836)	(0.0210)
Intercepts	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MAPE (%/mo.)	0.046	0.047	0.055	0.054	0.013	0.005	0.101	0.079	
H1 p-value	0.062	0.939	0.027	0.838	0.702	0.348	0.387	0.754	0.943
KZ p-value	0.000	0.600	0.204	0.070	0.000	0.042	0.076	0.750	0.000
N (assets)	11	6	11	12	13	5	6	6	70
N (beta, mos.)	126	126	126	126	126	126	126	126	
N (mean, mos.)	388	312	446	300	126	198	1133	359	

Standard errors in parentheses

Notes: This table reports estimates for the price of risk (λ in Equation (12)) from the various asset classes described in Internet Appendix Section K. "Neg. Fwd. CIP Ret." is the negative of the return on the AUD-JPY 1M-fwd 3M forward CIP trading strategy and "Int. Equity" is the intermediary equity return of He et al. (2017). Intercepts indicates an intercept is used for each asset class (one intercept per column, with eight in (9), which pools the first eight asset classes). MAPE is mean absolute pricing error of monthly returns. H1 p-value tests whether the price of the Fwd. CIP Ret. and Int. Equity risks are equal to the mean excess returns of those trading strategies. KZ p-value is the p-value of the Kleibergen and Zhan (2020) test rejecting reduced rank for the betas of the test assets. Standard errors are computed using GMM with the Newey-West kernel and a twelve-month bandwidth. Units are in percentage points.

Table A24: **Cross-sectional Asset Pricing Tests, USD-JPY**

	(1) US	(2) Sov	(3) FX	(4) Opt	(5) FwdArb	(6) CDS	(7) FF6	(8) Comm	(9) 1-8
Int. Equity	-0.380	0.586	2.711	0.443	0.610	1.232	1.056	0.124	0.470
	(0.406)	(1.439)	(0.782)	(0.821)	(7.816)	(1.035)	(0.395)	(1.425)	(0.530)
Neg. Fwd CIP Ret.	-0.0603	-0.0332	-0.0633	-0.0698	-0.0386	-0.0897	0.00587	-0.111	-0.0430
	(0.0363)	(0.0948)	(0.0478)	(0.0433)	(0.0326)	(0.120)	(0.137)	(0.255)	(0.0220)
Intercepts	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MAPE (%/mo.)	0.046	0.048	0.052	0.063	0.016	0.013	0.100	0.163	
H1 p-value	0.018	0.991	0.007	0.556	0.451	0.251	0.546	0.656	0.450
KZ p-value	0.000	0.632	0.329	0.004	0.000	0.012	0.023	0.896	0.000
N (assets)	11	6	11	12	13	5	6	6	70
N (beta, mos.)	126	126	126	126	126	126	126	126	
N (mean, mos.)	388	312	446	300	126	198	1133	359	

Standard errors in parentheses

Notes: This table reports estimates for the price of risk (λ in Equation (12)) from the various asset classes described in Internet Appendix Section K. "Neg. Fwd. CIP Ret." is the negative of the return on the USD-JPY 1M-fwd 3M forward CIP trading strategy and "Int. Equity" is the intermediary equity return of He et al. (2017). Intercepts indicates an intercept is used for each asset class (one intercept per column, with eight in (9), which pools the first eight asset classes). MAPE is mean absolute pricing error of monthly returns. H1 p-value tests whether the price of the Fwd. CIP Ret. and Int. Equity risks are equal to the mean excess returns of those trading strategies. KZ p-value is the p-value of the Kleibergen and Zhan (2020) test rejecting reduced rank for the betas of the test assets. Standard errors are computed using GMM with the Newey-West kernel and a twelve-month bandwidth. Units are in percentage points.

Table A25: **Cross-sectional Asset Pricing Tests, Dollar-Neutral Carry**

	(1) US	(2) Sov	(3) FX	(4) Opt	(5) FwdArb	(6) CDS	(7) FF6	(8) Comm	(9) 1-8
Int. Equity	-0.227	0.914	2.692	0.834	-2.541	1.567	0.785	0.543	0.547
	(0.414)	(0.913)	(0.807)	(0.764)	(6.219)	(1.245)	(0.851)	(0.924)	(0.544)
Neg. Fwd CIP Ret.	-0.0413	-0.0200	-0.0416	-0.0531	-0.0281	-0.0474	0.0351	-0.0736	-0.0350
	(0.0242)	(0.0402)	(0.0278)	(0.0248)	(0.0158)	(0.0809)	(0.0791)	(0.0684)	(0.0120)
Intercepts	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MAPE (%/mo.)	0.051	0.046	0.049	0.053	0.011	0.011	0.092	0.071	
H1 p-value	0.099	0.811	0.022	0.885	0.400	0.333	0.127	0.891	0.726
KZ p-value	0.000	0.397	0.190	0.046	0.002	0.318	0.215	0.729	0.000
N (assets)	11	6	11	12	13	5	6	6	70
N (beta, mos.)	126	126	126	126	126	126	126	126	
N (mean, mos.)	388	312	446	300	126	198	1133	359	

Standard errors in parentheses

Notes: This table reports estimates for the price of risk (λ in Equation (12)) from the various asset classes described in Internet Appendix Section K. "Neg. Fwd. CIP Ret." is the negative of the return on the Dollar-Neutral Carry 1M-fwd 3M forward CIP trading strategy and "Int. Equity" is the intermediary equity return of He et al. (2017). Intercepts indicates an intercept is used for each asset class (one intercept per column, with eight in (9), which pools the first eight asset classes). MAPE is mean absolute pricing error of monthly returns. H1 p-value tests whether the price of the Fwd. CIP Ret. and Int. Equity risks are equal to the mean excess returns of those trading strategies. KZ p-value is the p-value of the Kleibergen and Zhan (2020) test rejecting reduced rank for the betas of the test assets. Standard errors are computed using GMM with the Newey-West kernel and a twelve-month bandwidth. Units are in percentage points.

Table A26: **Cross-sectional Asset Pricing Tests, Dynamic Top Five Basis**

	(1) US	(2) Sov	(3) FX	(4) Opt	(5) FwdArb	(6) CDS	(7) FF6	(8) Comm	(9) 1-8
Int. Equity	-0.315	0.803	2.676	0.630	-1.846	1.109	0.949	0.357	0.469
	(0.411)	(1.013)	(0.804)	(0.764)	(8.076)	(1.141)	(0.753)	(1.068)	(0.539)
Neg. Fwd CIP Ret.	-0.0479	-0.0244	-0.0453	-0.0582	-0.0315	-0.0840	0.0400	-0.102	-0.0387
	(0.0283)	(0.0524)	(0.0320)	(0.0293)	(0.0241)	(0.0682)	(0.137)	(0.0657)	(0.0152)
Intercepts	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MAPE (%/mo.)	0.048	0.047	0.052	0.058	0.013	0.007	0.094	0.036	
H1 p-value	0.056	0.946	0.019	0.857	0.849	0.331	0.229	0.600	0.966
KZ p-value	0.000	0.492	0.175	0.014	0.001	0.105	0.176	0.798	0.000
N (assets)	11	6	11	12	13	5	6	6	70
N (beta, mos.)	126	126	126	126	126	126	126	126	
N (mean, mos.)	388	312	446	300	126	198	1133	359	

Standard errors in parentheses

Notes: This table reports estimates for the price of risk (λ in Equation (12)) from the various asset classes described in Internet Appendix Section K. "Neg. Fwd. CIP Ret." is the negative of the return on the Dynamic Top Five Basis 1M-fwd 3M forward CIP trading strategy and "Int. Equity" is the intermediary equity return of He et al. (2017). Intercepts indicates an intercept is used for each asset class (one intercept per column, with eight in (9), which pools the first eight asset classes). MAPE is mean absolute pricing error of monthly returns. H1 p-value tests whether the price of the Fwd. CIP Ret. and Int. Equity risks are equal to the mean excess returns of those trading strategies. KZ p-value is the p-value of the Kleibergen and Zhan (2020) test rejecting reduced rank for the betas of the test assets. Standard errors are computed using GMM with the Newey-West kernel and a twelve-month bandwidth. Units are in percentage points.

Table A27: **Cross-sectional Asset Pricing Tests, Static Top 6 Basis**

	(1) US	(2) Sov	(3) FX	(4) Opt	(5) FwdArb	(6) CDS	(7) FF6	(8) Comm	(9) 1-8
Int. Equity	-0.302	0.782	2.696	0.623	-1.749	1.197	0.940	0.501	0.478
	(0.410)	(1.034)	(0.798)	(0.765)	(8.046)	(1.183)	(0.736)	(1.130)	(0.547)
Neg. Fwd CIP Ret.	-0.0459	-0.0245	-0.0449	-0.0581	-0.0309	-0.0770	0.0322	-0.112	-0.0378
	(0.0271)	(0.0545)	(0.0316)	(0.0299)	(0.0241)	(0.0664)	(0.118)	(0.0781)	(0.0152)
Intercepts	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MAPE (%/mo.)	0.047	0.047	0.052	0.057	0.013	0.007	0.095	0.029	
H1 p-value	0.056	0.964	0.016	0.822	0.943	0.301	0.241	0.626	0.966
KZ p-value	0.000	0.535	0.189	0.017	0.001	0.090	0.106	0.855	0.000
N (assets)	11	6	11	12	13	5	6	6	70
N (beta, mos.)	126	126	126	126	126	126	126	126	
N (mean, mos.)	388	312	446	300	126	198	1133	359	

Standard errors in parentheses

Notes: This table reports estimates for the price of risk (λ in Equation (12)) from the various asset classes described in Internet Appendix Section K. "Neg. Fwd. CIP Ret." is the negative of the return on the Static Top 6 Basis 1M-fwd 3M forward CIP trading strategy and "Int. Equity" is the intermediary equity return of He et al. (2017). Intercepts indicates an intercept is used for each asset class (one intercept per column, with eight in (9), which pools the first eight asset classes). MAPE is mean absolute pricing error of monthly returns. H1 p-value tests whether the price of the Fwd. CIP Ret. and Int. Equity risks are equal to the mean excess returns of those trading strategies. KZ p-value is the p-value of the Kleibergen and Zhan (2020) test rejecting reduced rank for the betas of the test assets. Standard errors are computed using GMM with the Newey-West kernel and a twelve-month bandwidth. Units are in percentage points.

Table A28: **Cross-sectional Asset Pricing Tests, Common Sample**

	(1) US	(2) Sov	(3) FX	(4) Opt	(5) FwdArb	(6) CDS	(7) FF6	(8) Comm	(9) 1-8
Int. Equity	-0.353	-0.109	0.874	1.623	-1.476	1.928	-0.654	-1.248	0.241
	(0.757)	(1.039)	(0.841)	(0.978)	(8.123)	(2.080)	(1.655)	(1.709)	(0.799)
Fwd. CIP Ret. PC1	-0.0993	-0.0401	-0.0352	-0.0326	-0.0405	-0.0484	-0.107	-0.0832	-0.0525
	(0.0546)	(0.0525)	(0.0694)	(0.0527)	(0.0310)	(0.196)	(0.281)	(0.212)	(0.0201)
Intercepts	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MAPE (%/mo.)	0.062	0.036	0.079	0.044	0.014	0.030	0.150	0.237	
H1 p-value	0.097	0.533	0.972	0.472	0.954	0.121	0.477	0.057	0.326
KZ p-value	0.000	0.545	0.217	0.016	0.001	0.069	0.077	0.864	0.000
N (assets)	11	6	11	12	13	5	6	6	70
N (beta, mos.)	126	126	126	126	126	126	126	126	
N (mean, mos.)	126	126	126	126	126	126	126	126	

Standard errors in parentheses

Notes: This table reports estimates for the price of risk (λ in Equation (12)) from the various asset classes described in Internet Appendix Section K, using only Post-GFC data. "Fwd. CIP Ret. PC1" is the return of the first principal component of the 1M-fwd 3M forward CIP trading strategies described in the text and "Int. Equity" is the intermediary equity return of He et al. (2017). Intercepts indicates an intercept is used for each asset class (one intercept per column, with eight in (9), which pools the first eight asset classes). MAPE is mean absolute pricing error of monthly returns. H1 p-value tests whether the price of the Fwd. CIP Ret. PC1 and Int. Equity risks are equal to the mean excess returns of those trading strategies. KZ p-value is the p-value of the Kleibergen and Zhan (2020) test rejecting reduced rank for the betas of the test assets. Standard errors are computed using GMM with the Newey-West kernel and a twelve-month bandwidth. Units are in percentage points.

Table A29: **Cross-sectional Asset Pricing Tests, 2-Factor. AR(1) Residual**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	US	Sov	FX	Opt	FwdArb	CDS	FF6	Comm	1-8
Int. Equity	-0.305	0.818	2.789	0.786	-0.760	1.582	1.061	0.138	0.498
	(0.432)	(0.978)	(0.805)	(0.783)	(8.507)	(1.009)	(0.430)	(1.033)	(0.550)
Basis AR1 Residual	-0.0585	-0.0296	-0.0278	-0.113	-0.0527	-0.0574	-0.00940	-0.0789	-0.0561
	(0.0291)	(0.0442)	(0.0465)	(0.0938)	(0.0322)	(0.0511)	(0.139)	(0.0512)	(0.0282)
Intercepts	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MAPE (%/mo.)	0.045	0.044	0.059	0.064	0.015	0.007	0.102	0.095	
H1 p-value	0.023	0.808	0.004	0.795	0.874	0.289	0.312	0.650	0.845
KZ p-value	0.000	0.188	0.296	0.154	0.001	0.002	0.015	0.393	0.000
N (assets)	11	6	11	12	13	5	6	6	70
N (beta, mos.)	125	125	125	125	125	125	125	125	
N (mean, mos.)	388	312	446	300	126	198	1133	359	

Standard errors in parentheses

Notes: This table reports estimates for the price of risk (λ in Equation (12)) from the various asset classes described in Internet Appendix Section K. Basis AR1 Residual is the AR(1) residual of the AUD-JPY 3m OIS basis, and "Int. Equity" is the intermediary equity return of He et al. (2017). Intercepts indicates an intercept is used for each asset class (one intercept per column, with eight in (9), which pools the first eight asset classes). MAPE is mean absolute pricing error of monthly returns. H1 p-value tests whether the price of the Int. Equity risk is equal to its mean excess return. KZ p-value is the p-value of the Kleibergen and Zhan (2020) test rejecting reduced rank for the betas of the test assets. Standard errors are computed using GMM with the Newey-West kernel and a twelve-month bandwidth. Units are in percentage points.

Table A30: **Cross-sectional Asset Pricing Tests, 2-Factor. 1st PC of Other Arbs.**

	(1) US	(2) Sov	(3) FX	(4) Opt	(5) FwdArb	(6) CDS	(7) FF6	(8) Comm	(9) 1-8
Int. Equity	-0.709	0.181	3.188	0.498	6.054	1.053	0.221	0.105	0.759
	(0.423)	(1.330)	(1.113)	(1.610)	(3.429)	(2.933)	(1.021)	(0.711)	(0.482)
PC1 Residual	-0.0452	-0.0271	-0.0855	-0.0740	-0.0424	-0.101	-0.0634	0.0140	-0.0174
	(0.0202)	(0.0503)	(0.0553)	(0.106)	(0.0431)	(0.174)	(0.0578)	(0.0235)	(0.0206)
Intercepts	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MAPE (%/mo.)	0.053	0.047	0.054	0.069	0.015	0.010	0.101	0.211	
H1 p-value	0.002	0.766	0.016	0.952	0.115	0.873	0.714	0.478	0.701
KZ p-value	0.000	0.345	0.587	0.002	0.004	0.146	0.037	0.001	0.000
N (assets)	11	6	11	12	13	5	6	6	70
N (beta, mos.)	126	126	126	126	126	126	126	126	
N (mean, mos.)	388	312	446	300	126	198	1133	359	

Standard errors in parentheses

Notes: This table reports estimates for the price of risk (λ in Equation (12)) from the various asset classes described in Internet Appendix Section K. PC1 Residual is the AR(1) residual of the first principal components of the non-CIP arbitrages described in Section 4.1, scaled to have the same volatility as the AUD-JPY forward CIP return, and "Int. Equity" is the intermediary equity return of He et al. (2017). Intercepts indicates an intercept is used for each asset class (one intercept per column, with eight in (9), which pools the first eight asset classes). MAPE is mean absolute pricing error of monthly returns. H1 p-value tests whether the price of the Int. Equity risk is equal to its mean excess return. KZ p-value is the p-value of the Kleibergen and Zhan (2020) test rejecting reduced rank for the betas of the test assets. Standard errors are computed using GMM with the Newey-West kernel and a twelve-month bandwidth. Units are in percentage points.

Table A31: **Summary Statistics of CIP and Near-Arbitrage Bases**

Period	CIP	Bond-CDS	CDS-CDX	Tenor basis	Tsy-swap spread	Refco-Tsy spread	KfW-Bund spread	TIPS-Tsy spread
Pre-Crisis	2.8	-2.9	-1.0	0.1	-52.3	4.4	10.9	27.9
	(8.2)	(5.7)	(1.9)	(0.4)	(6.5)	(7.9)	(2.8)	(6.8)
Crisis	17.8	75.0	6.6	6.3	-11.4	60.6	51.2	50.1
	(25.8)	(79.8)	(12.4)	(3.4)	(36.0)	(35.0)	(20.3)	(35.9)
Post-Crisis	54.3	22.9	4.2	10.0	25.4	44.0	28.5	27.6
	(28.3)	(16.3)	(5.0)	(2.9)	(15.2)	(12.6)	(17.4)	(8.1)

Notes: This table reports the mean and standard deviation of the AUD-JPY cross-currency basis and seven near-arbitrages, in basis points. "AUD-JPY Basis" denotes the OIS-based 3M tenor classic carry (AUD-JPY) cross-currency basis. "Bond-CDS" denotes the 5-year spread between North American investment grade corporate bonds and CDS spreads. "CDS-CDX" denotes the 5-year spread between the composite sperad of 125 constituents of the NA.IG.CDX index and the quoted spread on the CDX index. "Tenor Basis" denotes the 5-year 1-month versus 3-month Libor tenor basis swap spread. "Tsy-swap spread" denotes the 30-year spread between the U.S. Treasury over the interest rate swap. "Refco-Tsy" denotes the 5-year spread between the yield on Resolution Financing Corporation and the US Treasury. "KfW-Bund" denotes the 5-year spread between the yield on euro-denominated KfW bonds and German bunds. "TIPS-Tsy" refers the 5-year spread between the yield on the TIPS and the yield on the asset swap package consisting of nominal Treasurys and inflation swaps. All statistics are reported by period: Pre-GFC is 2005-01-01 to 2007-06-30, GFC is 2007-07-01 to 2010-06-30, and Post-GFC is 2010-07-01 to 2020-12-31. More details on these near-arbitrages can be found in Internet Appendix G.

Table A32: **Price of Risk and SDF Parameters**

	Intermediary Equity Return	PC of Fwd. CIP Trading Strategy Ret.
Price of risk	0.592	0.046
	(0.282)	(0.017)
SDF parameters	-0.155	246.709
	(1.461)	(62.986)

Notes: This table reports the estimated price of risk and SDF parameters on the two proposed factors. Price of risk is reported in percentage points. The price of risk on intermediary equity return is estimated using monthly return from January 1970 through December 2020. The price of risk on the forward CIP trading strategy return is estimated using daily observations of monthly return from 2010-07-01 to 2020-12-31. Newey-West standard errors are reported in parentheses, where the overlapping bandwidth is chosen by the Newey-West (1994) selection procedure. *, **, and *** denote significance levels at 10%, 5%, and 1% confidence levels. More details on the estimation can be found in Internet Appendix H.