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LEVERAGE DEMAND AND DEVIATIONS FROM THE LAW OF ONE PRICE

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ABSTRACT

Deviations from the law of one price between futures and spot prices, known as bases, reflect the difference between interest rates implied in futures prices and benchmark borrowing rates. These differences are driven by intermediaries' cost of capital and the amount of leverage demand for an asset. Focusing on leverage demand, we find that bases negatively predict futures and spot market returns with the same sign in both global equities and currencies. This evidence is consistent with bases capturing uninformed leverage demand. We investigate the source of this demand in both markets using dealer and institutional positions data, securities lending fees, and foreign capital flows and find that the return predictability represents compensation to intermediaries for meeting liquidity and hedging demand. Our results have broader implications for understanding the interest rates embedded in derivatives prices.

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Introduction

We study deviations from the textbook law of one price in equity index futures and currency forward markets, known as bases. The basis is the futures price minus the synthetic fair-value futures price implied by the spot price and the benchmark borrowing rate.[1] A common interpretation is that bases reflect additional costs that financial intermediaries face to provide leverage that deviate from benchmark borrowing rates. These costs stem from frictions and constraints faced by financial intermediaries, and are often ascribed to intermediary balance sheet costs. However, financing costs and the basis are also affected by the relative demand for leverage to be intermediated.[2] Specifically, if the demand for leveraged asset exposure exceeds the supply intermediaries are comfortable providing at current rates, then intermediaries will raise borrowing rates embedded within leveraged assets. We refer to these potential demand-supply imbalances as "demand effects," (assuming shocks come from the demand side). Intermediary financing costs will increase with the amount of demand for leveraged asset exposure, where long (short) futures demand implies a more positive (negative) basis. Rather than focus on the cost of financial intermediation implied by the basis, we focus on the demand for leveraged asset exposure that gives rise to the basis.

Focusing on the demand side allows us to sign the basis and explain cross-sectional variation in the magnitude of bases across assets (for different equity indices and different currencies). Such heterogeneity is difficult to explain by balance sheet costs alone. While the link between bases and leverage demand is implicitly assumed in work on intermediary financing costs, it has not been extensively explored. We focus on this link to measure leverage demand and its sources, enabling us to better understand what gives rise to pricing deviations and the motivations for trading in futures and forwards in these markets. An implication of demand effects is that bases should predict not only futures returns, but also underlying spot market returns, and with the same sign. We examine the relation between bases and subsequent returns in both futures and spot markets, providing a unique test of leverage demand effects. A central question is whether the demand for

[1]The existence of bases in equity index futures is documented by Cornell and French (1983); Figlewski (1984); MacKinlay and Ramaswamy (1988); Harris (1989); Miller et al. (1994); Yadav and Pope (1994) and Chen et al. (1995), who posit different theories regarding whether the basis represents a true arbitrage opportunity. Roll et al. (2007) link the bases in the now-defunct NYSE Composite futures market with market liquidity.

[2]Deviations from the law of one price related to financing frictions have been documented in a variety of settings, including equity carve outs (Lamont and Thaler (2003)), equity index options (Constantinides and Lian (2015), Chen et al. (2018), Golez et al. (2018)), currencies (Garleanu and Pedersen (2011); Borio et al. (2016); Du et al. (2018)), TIPS/treasuries (Fleckenstein et al. (2014)), CDS/bonds (Duffie (2010); Garleanu and Pedersen (2011)) and corporate bonds (Lewis et al. (2017)).

leverage comes from informed or uninformed investors. Informed demand predicts the direction of demand (and the basis) to be positively related to subsequent asset returns, while uninformed demand predicts a negative relation to future asset returns.

We find strong evidence that bases negatively predict *both* futures returns *and* spot returns with the same sign, in both the cross-section and time-series in both currency and global equity index markets. This evidence is consistent with uninformed demand imbalances in both markets driving variation in the basis. Markets where futures prices are "expensive" relative to their hypothetical fair values have lower average returns and markets where futures prices are "cheap" relative to their synthetic fair values have higher average returns. This relation holds for a given equity index and currency over time as well as across equity indices and currencies at a point in time. The magnitude of the return predictability far exceeds that from simple convergence of the basis towards zero. Since 2007, the return predictability is five times greater in global equity markets and nearly fifteen times greater in currency markets than the returns from bases converging to zero. Moreover, if futures return predictability is driven solely by basis convergence, then spot market returns should be positively, not negatively, related to the basis. Finally, the negative relationship between bases and subsequent returns is present even when the magnitude of the basis is small due to lower financing frictions. For example, tiny violations of covered interest rate parity (CIP) before the Global Financial Crisis still have substantial return predictability for currency returns, further emphasizing the interaction between financing costs and leverage demand that matter for bases.

In both currency and equity markets, positive bases imply long leverage demand and higher financing costs for intermediaries to meet that demand. This leverage demand appears to be uninformed, as opposed to informed demand, because it generates negative return predictability. We consider the source of the return predictability in both global equity and currency markets to understand the nature of demand embedded in the basis. In equity index futures markets, we posit that part of the demand comes from investors rebalancing their equity exposure, which is reflected in cash equity markets through index arbitrage. The negative return predictability may therefore reflect a premium for liquidity provision provided by those holding positions on the opposite side, consistent with Kyle (1985) and Grossman and Miller (1988). In currency markets, end-user demand for currency forwards and futures often comes from a hedging motive. We find that bases in currencies capture information about foreign investment flows, where the negative return predictability of the basis may reflect compensation to financiers willing to bear currency risk to facilitate the flow of international capital, consistent with recent theoretical and empirical work (e.g. Gabaix and Maggiori (2015) and Corte et al. (2016)).

To corroborate these motives, we analyze the relation between direct proxies for leverage demand and bases in both markets. We examine data on dealer inventories and investor positions from the U.S. Commodity Futures Trading Commission (CFTC) for equity index futures. Dealer net positioning is strongly negatively related to the basis, while end-user net positioning of levered funds and institutions is positively related to the basis. Across equity indices, the basis varies positively with the strength of opposing positions between dealers and end-users, and, for a given futures contract, variation in the basis over time corresponds with variation in the size of opposing positions between dealers and other traders. These cross-sectional and time-series results are consistent with demand for leveraged equity exposure being strongly related to the size of the futures-spot basis.

Another link between the basis and demand for leverage in global equity markets is evident in securities lending fees and the availability of lendable shares. The connection between the basis and securities lending arises from index arbitrageurs facilitating trading in equity index futures markets, as illustrated in Fig. 1. Dealers holding a position in futures to accommodate leverage demand will offset their market exposure by taking an opposite position in the cash equity market. If capital constrained, dealers will seek financing for their hedge positions, which is often cheapest to do by lending out shares in exchange for cash, with the financing costs for providing long futures exposure decreasing in the security lending fee.[3] When faced with long demand in futures markets, dealers will increase the supply of shares available to borrow in security lending markets, decreasing security lending fees and increasing the financing costs of futures market making. As a result, dealer financing costs are increasing with long leverage demand, as security lending fees decrease. The signs are reversed when dealers face substantial demand for shorting futures. Hence, a more positive (negative) basis corresponds to stronger long (short) futures demand.[4] We provide evidence consistent with this mechanism, using data on securities lending for global equi-

[3]Securities lending can offer dealers more attractive financing since dealers may deduct a security lending fee from their cash borrowing rate. Song (2016) presents a model in which securities lending/equity repo financing is the preferred financing strategy for intermediaries in equity derivatives markets. Omprakash (2014) similarly argues that equity repo financing is the preferred financing strategy for dealers in equity derivatives.

[4]The demand for financing need not originate in the futures markets. If market participants can directly obtain leverage via the share lending market, often intermediated by prime brokers, this, too, increases the supply of shares available to borrow, thus increasing financing costs. As a result, index arbitrageurs face higher financing costs, and the futures basis similarly increases.

ties. Moreover, this demand channel can explain the sign and magnitude of the basis over time and across assets.

For currencies, we connect bases to leverage demand via currency hedging due to foreign investment. Investors wishing to hedge their currency exposure from foreign investments will go long their home currency and short the currencies of their foreign investments using currency derivatives. The increased hedging demand increases the financing costs faced by financial intermediaries who hold offsetting currency forward positions that they hedge in the spot market. Using the futures positions of institutional investors in currency markets and data on international capital flows to proxy for hedging demand, we find consistent evidence that currency hedging demand is strongly associated with cross-sectional variation in cross-currency bases.[5] This evidence builds on the work of Du et al. (2018), who link CIP deviations to intermediary financing costs, with an implicit underlying assumption that there exist persistent imbalances in international investment demand and funding supply across currencies.[6] We provide evidence identifying hedging demand across currencies to augment their story, and show that variation in demand imbalances (using our proxies) captures variation in bases and its subsequent return predictability.

Our focus on the implied demand embedded in the basis and violations of the law of one price also has implications for recent work on inferring interest rates from derivatives prices. For example, Binsbergen et al. (2019) infer borrowing rates from option contracts on the S&P 500 (and other indices and commodities) and compare them to US Treasury yields to back out a "convenience yield" embedded in Treasuries. In an analogous fashion, we extract interest rates embedded in futures prices, but argue that the spreads between derivative-implied interest rates and benchmark borrowing rates also contain information about leverage demand for an asset. We find a strong relationship between our 3-month futures implied interest rates and option-implied interest rates at longer maturities from Binsbergen et al. (2019). Using dealer futures positions to proxy for leverage demand, we estimate that the component of the 3-month futures implied interest rate related to leverage demand is small, but not inconsequential, compared to the convenience yield that Binsbergen et al. (2019) estimate from option-implied interest rates. For the longer maturity

[5] Borio et al. (2016) and Sushko et al. (2017) study cross-currency bases and suggest that hedging demand from foreign banks, institutional investors, and US firms issuing foreign corporate debt may be substantial drivers of cross-currency bases. Liao (2018) studies covered interest rate parity violations and corporate bond issuance in more depth.

[6] In recent work, Andersen et al. (2019) argue that an important component of intermediary financing costs that contribute to CIP deviations are debt funding costs that dealer banks face, which have increased post-financial crisis in large part due to the increase in dealer banks credit spreads.

option-implied interest rates from Binsbergen et al. (2019), the relation is weaker.

Our results offer further evidence for the role that financing costs play in determining asset prices, particularly violations of the law of one price, and its important interaction with asset demand. We connect the literature on intermediation costs to the literature on end-user demand, dealer inventories, and asset prices (De Roon et al. (2000); Chordia et al. (2002); Bollen and Whaley (2004); Garleanu et al. (2009); Greenwood and Vayanos (2014); Hendershott and Menkveld (2014); Boons and Prado (2019); Koijen and Yogo (2019), and He et al. (2019)), making clear that financing rates and asset demand are intertwined.[7] We also relate to recent work on covered interest rate parity violations and exchange rate determination. Jiang et al. (2018) and Krishnamurthy and Lustig (2019) link exchange rates versus the US dollar to foreign investor convenience yields for US treasury bonds, which they measure via the "Treasury Basis" related to CIP deviations. They find that the Treasury Basis has long-horizon (three to five-year) return predictability for the US dollar versus other currencies. Our paper differs from these studies in that we focus on the cross-sectional relationship between CIP violations and short-horizon (monthly) currency returns.[8]

Finally, our paper is related to recent work on the role of financial intermediaries in asset pricing. The existence of bases in both currency and equity markets reflects the fact that the cost of capital for intermediaries in these markets is different from simple uncollateralized borrowing rates (Garleanu and Pedersen (2011)), due to both financial frictions and demand for leverage in the asset. The return predictability of bases reflects financial intermediaries with limited risk-bearing capacity requiring compensation to provide liquidity in these markets to meet demand. The results suggest that the risk-bearing capacity of intermediaries plays an important role in determining asset prices, consistent with a growing body of work (e.g. He and Krishnamurthy (2013); Brunnermeier and Sannikov (2014); Adrian et al. (2014) and He et al. (2017)).

The rest of the paper is organized as follows. Section 1 presents the data and methodology for calculating the futures-spot basis in equity index and currency markets. Section 2 analyzes the relationship between futures-spot bases, covered interest rate parity violations, and expected returns in global equity and currency markets. Section 3 examines the interaction between the basis and demand for leveraged asset exposure, finding evidence consistent with uninformed liq-

[7] In a similar spirit to our paper, Klingler and Sundaresan (2019) link negative swap-spreads (another type of basis) with persistent demand for swaps by underfunded pension plans and dealers' balance sheet constraints.

[8] The sign of the currency return predictability from CIP violations is opposite in our paper. The convenience yield or "Treasury Basis" predicts returns with opposite signs at short versus long horizons.

uidity demand driving variation in the basis and subsequent return predictability. Section 4 relates our findings to the interest rates implied in derivative securities. Section 5 examines the relation between basis return predictability and other well-known return predictors. Section 6 concludes.

1 Data and Methodology

We describe the data and methodology for computing the basis in equity index futures and currency markets and present summary statistics.

1.1 Equity Index Futures Data

We obtain listed futures on eighteen developed market equity indices: S&P 500 (US), NASDAQ (NASDAQ), Russell 2000 (USRU2K), S&P 400 MidCap (USSPMC), Dow Jones Industrial Average (DJIA), S&P TSE 60 (Canada, CN), FTSE 100 (United Kingdom, UK), EUROSTOXX (European Union, EUROSTOXX), CAC40 (France, FR), DAX (Germany, BD), IBEX (Spain, ES), FTSE MIB (Italy, IT), AEX (Netherlands, NL), Hangseng (Hong Kong, HK), Topix (Japan, JP), OMXS30 (Sweden, SD), SMI (Switzerland, SW), and ASX SPI 200 (Australia, AU). The sample period is January 2000 to December 2017, where we have intraday pricing data used to compute the basis. We compute returns to futures contracts on each index excluding returns on collateral from transacting in futures contracts, which are essentially returns in excess of the risk-free rate.

1.1.1 Computing the Basis for Equity Index Futures

We construct the basis for each index in our sample based on the no-arbitrage relationship between futures and spot prices,

$$\hat{F}_t = S_t \left(1 + r_t^f\right) - \mathbb{E}_t^Q \left(D_{t+1}\right)$$

where S_t is the observed spot price, $\hat{F}_t$ is the no-arbitrage implied futures price, r^f is the benchmark interest rate, and $\mathbb{E}_t^Q \left(D_{t+1}\right)$ is the expected dividends in period $t+1$ under the risk-neutral probability measure.[9] For the benchmark borrowing rate, we use the local interbank offer rate for

[9] We use expectations of dividends under the physical measure to proxy for expectations of dividends under the risk-neutral measure (which we generally do not observe for most of our sample). In all of the markets we consider, dividends are announced one to three months prior to the ex-date, which matches the maturity of most of the contracts we consider. We therefore expect the majority of dividends for an index to be known in the calculation of the basis. In

each market, constructed by interpolating listed rates to match the maturity of the futures contract. The no-arbitrage relationship between futures and spot prices assumes that dealers are able to finance their market-making activities at the local interbank lending rate, an assumption that is often not true in practice, which gives rise to the bases we observe. From January 2007 through the end of our sample, we use point-in-time forecasts of index dividends provided by Goldman Sachs as our measure of dividend expectations. From 2000 through 2006, we use the realized dividends of an index from t to $t+1$ to proxy for dividend expectations. We show in the internet appendix A.3 that our results are virtually unaffected by using realized versus expected dividends.[10]

We construct the basis as the difference between the observed futures prices, F_t, and the fair-value futures prices, $\hat{F}_t$, normalized by the spot price and time-to-maturity of the contract.

$$\text{Basis}_t = \frac{F_t - \hat{F}_t}{S_t \times TTM} = r_t^{f*} - r_t^f. \tag{1}$$

We normalize by time-to-maturity for comparability across indices with different expiration dates and to capture the decay of the basis as the contract approaches expiration.[11] Equation (1) can be interpreted as the annualized difference between the expected return to holding futures on an index and the expected return to holding the stocks of an index in excess of the local interbank lending rate, which is also the difference between the annualized interest rate implied in the price of a futures contract, r_t^{f*}, and the annualized benchmark interest rate, r_t^f.

To construct the basis, we use pricing data from Thompson Reuters Tick History (TRTH). For spot index prices, the database contains the last traded prices of each index, aggregated from the last traded prices of the individual constituents in the index, provided on a minute-by-minute frequency. For futures prices, the database contains tick-level data, where we compute minute-by-minute futures prices by taking the mid point from the last bid and ask quotes, and then calculate a daily value of the basis as the average of the minute-by-minute observations. Averaging minute-by-minute prices reduces estimation error and better controls for asynchronous closing prices in

internet appendix A.2, we perform back-of-the-envelope calculations of the impact of using expectations of dividends under the physical measure to proxy for dividends under the risk-neutral measure. The estimated impact is small.

[10]Using annualized dividend yields to proxy for expected dividends can be problematic for a number of indices due to seasonalities in dividend payments. We argue and show that the use of realized dividends to proxy for expected dividends likely understates the relationship between the basis and expected returns in equity index futures. In internet appendix A.3, we replicate our results in the post-2007 sample period using bases constructed with realized dividends and find very similar results.

[11]MacKinlay and Ramaswamy (1988) and Chen et al. (1995) find that the magnitude of the S&P 500 basis is approximately proportional to its time-to-maturity. We find a similar result across all equity indices.

futures markets and cash equity markets.[12]

For each equity index, we construct a series that combines the bases of individual futures contracts with different expirations. We use the near contract until ten days before expiration, where most of the trading takes place in this market. Within ten days to expiration, we use a linear combination of the basis values of the nearest and the second-nearest contracts, with the weight on the front contract transferring linearly to the back contract as the front contract nears maturity. This choice is meant to mitigate spikes in the basis that occur around contract expirations due to a combination of trading behavior around the "roll period" (when the majority of market activity transfers from the near contract to the second contract), as well as due to potential measurement error coming from scaling by maturity for contracts close to expiration. Results are robust to alternative methodological choices for combining contract-level basis values, such as using an open-interest weighted combination of the basis values, using the basis value of the nearest expiration contract until it's expiration, or calculating a fixed maturity basis for each index by interpolating the basis values of different maturity contracts.

1.2 Currency Data

Our sample of currencies consists of G10 currencies, splicing the Euro with the Deutsche Mark in the pre-Euro period. We compute returns from currency forward contracts, where currency returns are all U.S. dollar-denominated and implicitly include the local interest rate differential.

We measure LIBOR-based CIP deviations using the no-arbitrage relationship between currency forward and spot rates, from the perspective of an investor seeking to buy foreign currency and sell US dollars forward. The CIP condition is expressed as,

$$\hat{F}_t = S_t \frac{1 + r_t^{US}}{1 + r_t^{foreign}},$$

where $\hat{F}_t$ denotes the forward rate to buy a foreign currency and sell US dollars, r_t^{US} denotes the US risk-free rate, $r_t^{foreign}$ denotes the local risk free rate earned on the foreign currency, and S_t denotes the spot exchange rate (dollars per unit of foreign currency). We construct the cross-currency basis as the difference between the observed forward rate at time t, F_t, and the fair value forward rate at

[12] For example, spot trading S&P500 index constituents ends at 4:00 PM, while futures markets close at 4:15 PM.

time t, normalized by the exchange rate and forward maturity:

$$\text{fx basis}_t = \frac{F_t - \hat{F}_t}{S_t \times TTM} = \left(r_t^{US*} - r_t^{US}\right) \frac{1}{1 + r_t^{foreign}}. \tag{2}$$

We construct a panel of cross-currency bases using 3-month forward rates and exchange rates that combines pricing data from WM/Reuters pre-1999 with pricing data provided by Citi Bank post-1999 measured at the close of London markets on each day. We truncate the New Zealand Dollar and Canadian Dollar data for the early part of our sample due to concerns about asynchronous snap times of the spot prices and forward prices. As we do in the construction of equity index futures bases, we assume the local IBOR rate to be the local risk-free rate for all currencies in our sample. Equation (2) shows that the cross-currency basis is equal to the difference between the USD borrowing rate implied in currency forwards and the benchmark USD borrowing rate, normalized by a scaling factor that is close to one, $\left(1 + r_t^{foreign}\right)^{-1}$. Since bases are constructed relative to the USD, we set the basis value corresponding to the USD to be zero. Table A.1 in the internet appendix lists the indices and currencies in our sample and their starting dates.

1.3 Summary Statistics of the Basis in Global Equities and Currencies

Table 1 reports summary statistics for the futures-spot basis in global equity and currency markets. We report summary statistics for the full sample, as well as for three sub-samples: January 1989 to December 1999, January 2000 (when our global equity basis sample starts) to June 2007, and July 2007 to December 2017 (when substantial deviations from covered interest rate parity emerge in currency markets). The average bases, average absolute value of bases, and average time-series and cross-sectional standard deviations of bases are reported (in annualized basis points).[13]

For global equities, the average basis is -1 bp, but the average absolute value of the basis is 57 bps, average time-series standard deviation is 92 bps, and average cross-sectional standard deviation is 90 bps. These numbers suggest that, while bases are close to zero on average in global equity markets, there is substantial variation in the basis over time and across indices. The magnitude and variation of bases is lower in the post-2007 period than in the 2000-2007 period.

For currencies, the average basis value is 7 bps, with the average absolute value of the basis being 13 bps, the average time-series standard deviation 23 bps, and the average cross-sectional

[13] We also report asset-by-asset summary statistics of the basis in the internet appendix Table A.1 and Table A.2.

standard deviation 15 bps. Consistent with the literature, the magnitude of the basis is elevated post-2007, where the average basis is 15 bps, and average absolute basis is 20 bps, compared to only an average 3 bps and average absolute basis of less than 5 bps in the 2000-2007 subsample. In the 1989-2000 sub-sample, the average value of the basis is 0.06, but the average absolute value of the basis is 12 bps, average time-series standard deviation is 25 bps, and average cross-sectional standard deviation is 18 bps. There is significant time- and cross-sectional variation in cross-currency bases, but also distinct "regimes", where the period 2000-2007 shows very little CIP deviations compared to the pre-2000 and post-2007 periods. We exploit this variation to identify demand effects separate from financing frictions.

Comparing bases in currencies versus equities, bases are an order of magnitude larger in global equity index markets. Even in the recent period, where deviations from covered interest rate parity have been "large", these deviations are still less than half the size of the bases in global equity markets over the same period. One reason for these differences is due to the frictions associated with financing positions in currency versus equity markets. Currency markets are money markets, where the primary frictions that generate covered interest rate parity violations in recent times are related to the cost of bank balance sheet space (e.g. Du et al. (2018)). In global equity markets, however, there are additional frictions that increase the cost of leverage. One such friction comes from securities lending, which we explore in more depth to gain further insight into what drives bases and why they predict returns.

Using the variation in bases across time and across assets, as well as differences between the currency and equity markets, we attempt to identify leverage demand embedded in the basis and understand its interaction with financing frictions that give rise to these pricing violations and subsequent return predictability. We begin with the relation between bases and expected returns in each market, and then examine data on net positions, financing costs, and lending fees to help further identify what drives bases.

2 The Basis and Expected Returns

We begin by studying the relationship between future-spot bases and expected returns. We discuss several theories that could give rise to bases and their predictions for expected returns in both futures and spot markets. We then examine empirically how the basis predicts returns in both markets to distinguish among the theories.

2.1 Theoretical Predictions

We start with the simple case where the basis represents an arbitrage opportunity. At maturity (T), the futures contract provides delivery of the underlying asset (or its cash equivalent), and hence has to equal the spot price ($F_T = S_T$).

Theory 1: The basis represents an arbitrage opportunity. Assuming arbitrageurs can finance a position in the spot market at the benchmark interest rate and that shorting and holding frictions are negligible, a non-zero basis implies an arbitrage opportunity, where arbitrageurs can buy or sell futures contracts, borrow or lend cash, and purchase or sell equal notional amounts of the underlying asset in spot markets until the basis is eliminated. In this scenario, there is a temporary mispricing that arbitrageurs close. The duration of the basis or speed with which it closes depends on the speed of arbitrage capital (Shleifer and Vishny (1997); Duffie (2010)). This theory does not state where the mispricing comes from, but merely states that given a non-zero basis arbitrageurs will take action to eliminate it.

Arbitrage activity implies that the basis will forecast futures prices with a negative sign and forecast spot prices with a positive sign as the basis converges to zero over time. This implication also follows from equations (1) and (2) and $F_T = S_T$, assuming both the futures price and spot price converge. It is also possible that only one of the markets is mispriced, in which case convergence happens in one market but not the other, leading to a zero correlation between the basis and returns in the other market. For example, if the futures contract is mispriced, then the futures price may converge to the spot price, while the spot price may remain unchanged, or vice versa. Hence, we get the following implications:

$$\text{cov}(\frac{F_T}{F_t}, Basis_t) \leq 0 \text{ and } \text{cov}(\frac{S_T}{S_t}, Basis_t) \geq 0. \quad (3)$$

More formally, if we run the following regressions,

$$\frac{F_T}{F_t} = a + c(Basis_t) + e_t \quad (4)$$

$$\frac{S_T}{S_t} = \alpha + \gamma(Basis_t) + u_t \quad (5)$$

we get the following predictions:

Prediction 1: If the basis represents an arbitrage opportunity and there are no limits to arbitrage, then $c \leq 0$ and $\gamma \geq 0$ and $|c| + |\gamma| = 1$.

The basis should predict the returns of futures and spot prices in opposite directions. The signs on c and γ follow from above, but in addition, if we get full convergence between the futures and spot markets, then the sum of the absolute value of the coefficients has to equal one.

Under the previous theory, arbitrageurs can borrow at the specified benchmark interest rate and execute a true arbitrage opportunity when there is a non-zero basis. The next two theories we examine argue that the basis, rather than representing a true arbitrage opportunity, instead captures a difference between the benchmark interest rate and the rate at which the marginal arbitrageur can borrow in order to finance futures-spot arbitrage. If there are financing frictions that create a wedge between the interest rates arbitrageurs face and the prevailing interest rate in the economy, then executing the trade is no longer costless. The basis, therefore, represents the additional financing cost arbitrageurs face. The next two theories offer different reasons why the marginal arbitrageur's financing rate differs from the benchmark rate.

Theory 2: The basis represents additional financing costs facing the marginal arbitrageur unrelated to supply and demand imbalances for leverage. Under this theory, bases merely reflect financing frictions relative to the assumed benchmark borrowing rate. For example, if arbitrageurs actually finance positions at a different rate than the local interbank offer rate (such as interbank deposit rates or Commercial Paper rates), we would measure a non-zero basis.[14] Under this interpretation, as the futures contract approaches maturity, the basis will again converge to zero and the futures price will converge to the spot price since financing costs approach zero at time T. Hence, the relation between the basis and futures expected returns will again be negative, cov$(\frac{F_T}{F_t}, Basis_t) \leq 0$. However, since the basis only reflects financing cost differences between the futures contract and the synthetic future/replicating portfolio (and is assumed to be unrelated to demand imbalances), the relation between the basis and spot returns is zero, cov$(\frac{S_T}{S_t}, Basis_t) = 0$. The implications from regression equations (4) and (5) are:

Prediction 2: If the basis only reflects financing frictions, then $c = -1$ and $\gamma = 0$.

In this case, not only is $c < 0$, but this theory makes a stronger prediction that $c = -1$ since the spot price, S_t, will be independent of the basis if the only wedge in the arbitrage relation at time t

[14] Rime et al. (2017)) suggest that CIP deviations are negligible when using interbank deposit rates and commercial paper rates, which they argue more closely reflect the rates that most major market participants can finance arbitrage. Their work, however, also traces the emergence of CIP deviations to the types of supply and demand imbalances we discuss in Theory 3.

is financing frictions (unrelated to leverage demand). To see this, take the simple case where the spot price does not change, $S_t = S_T$, and the basis goes to zero as the futures price converges to S_T at contract maturity.

An additional implication of this theory is that if the same marginal arbitrageur operates in each market, then there should be no cross-sectional variation in bases for equity futures sold in the same country (e.g., all U.S. equity indices should have the same basis) and all currencies versus the U.S. dollar should have the same basis. To capture heterogeneity in bases within a given market under this theory, an additional assumption that different marginal arbitrageurs operate in different indices within the same market, and for different foreign currencies relative to the dollar, is required. The cross-sectional variation in bases would therefore reflect the cross-sectional differences in marginal investor funding rates, which based on the summary statistics in Table 1 appears to be implausibly large – something we investigate further below.

Theory 3: The basis represents demand-supply imbalances that impact financing rates. If demand for leverage outstrips intermediaries' ability to supply leverage at current rates, then intermediaries will raise rates, creating a deviation between futures prices and synthetic futures that gives rise to the basis. This interpretation is broadly given to CIP deviations in currency markets. For example, Du et al. (2018) relate CIP violations to regulatory bank capital requirements that create a wedge between intermediary financing costs and benchmark borrowing rates, while Andersen et al. (2019) link wedges between intermediary financing costs and benchmark borrowing rates to dealer bank debt funding costs. Taking this idea one step further, if leverage demand is transmitted to spot demand via intermediation and arbitrage activity (see the mechanics of futures trading in Fig. 1), then the basis will also predict spot returns in addition to futures returns. In this sense, futures and spot markets are linked by no-arbitrage, but the interest rate used in the no-arbitrage identity will vary with leverage demand.

The sign of the predicted relation of the basis with subsequent futures and spot market returns depends on whether the demand for leverage is informed or uninformed. Informed demand implies that the basis positively predicts spot market returns. Futures returns will also be positively related to the basis through this demand effect, but will be partially offset by the negative relation between financing costs and futures returns. This leads to the following prediction,

> **Prediction 3a:** If the basis reflects financing frictions and *informed* demand imbalances, then $c > -1$ and $\gamma > 0$, with $\gamma > c$.

If, on the other hand, the demand for leveraged asset exposure comes from uninformed investors, due to hedging motives for example, then the basis will negatively predict spot returns and exacerbate the negative relation between the basis and futures returns. The negative relation stems from liquidity providers who take economic exposures opposite the uninformed demand and require compensation, consistent with liquidity provision (Kyle (1985); Grossman and Miller (1988)).

> **Prediction 3b:** If the basis reflects financing frictions and *uninformed* demand imbalances, then $c < -1$ and $\gamma < 0$, with $c < \gamma$.

This theory also makes predictions about cross-sectional variation in bases and return predictability, where variation in demand-supply imbalances should match variation in bases and generate additional return predictability. This theory, therefore, has hope in explaining the variation in bases we see across assets in Table 1. An implication we test below.

Theory 4: Segmented Markets. Finally, an alternative theory is that futures and spot markets are segmented so that futures-spot arbitrage is impaired. Under this theory, there can be separate demand imbalances in the spot and futures markets that could generate return predictability of either sign in either market, and generate them independently. This theory is not particularly appealing since it can accommodate almost any pattern of return predictability and relies on arbitrage failing in these markets because investors in one market do not pay attention to the other market. Given that the markets we examine – equity index futures and currency forwards – are large and liquid with healthy arbitrage forces connecting their spot and futures markets, this premise seems to be a poor description of how these markets operate.

It is worth noting that these theories are not mutually exclusive. For example, it may be the case that futures-spot arbitrage works reasonably well but is slightly impaired. In this case, leverage demand in futures markets is mostly transmitted into demand in the spot market (consistent with Theory 3), but the basis may also represent a small arbitrage opportunity (consistent with Theory 1).

A key distinguishing feature among the theories, and the degree to which they affect asset prices, is whether the return predictability for futures and spot prices has the same or opposite sign. Demand-based theories imply return predictability of the same sign, while pure arbitrage and financing costs imply opposite signs for futures versus spot return predictability. We test these predictions using detailed data in global equity index and currency markets, which are two of the largest and most liquid financial markets, and use the above theories to interpret our results.

2.2 The Return Predictability of the Basis

To test the predictions above, we run a set of panel regressions within each asset class of the form,

$$r_{i,t+1}^{fut} = a_i + b_t + cBasis_{i,t} + \epsilon_{i,t+1} \tag{6}$$

$$r_{i,t+1}^{spot} - r_{f,t} = \alpha_i + \beta_t + \gamma Basis_{i,t} + \eta_{i,t+1} \tag{7}$$

where r_{t+1}^i is the return of asset i, a_i and α_i are asset-specific intercepts, b_t and β_t are time fixed effects, and $Basis_{i,t}$ is the futures-spot basis for asset i measured in the previous period. Regressions are estimated using weekly return data, with the basis scaled to be a weekly rate. We report regression results over the full sample, and also for the sub-samples listed in Table 1. Since bases differ in magnitude and variance across the sub-samples, we run GLS regressions for the full sample, with observations weighted inversely by the variance of the basis in each sub-sample.[15] Standard errors are clustered by asset and time.

Panel A of Table 2 reports regression results for global equity indexes. The first row reports regression coefficients for the full sample. The first four columns correspond to regressions where the dependent variable is the futures return for a given market. In all specifications, the coefficients on the basis are significant and negative, with values ranging from approximately -4.1 (t-statistic of -3.67) when including time and entity fixed effects to approximately -5.2 with no fixed effects (t-statistic of -2.63). These coefficients are also significantly less than -1, consistent with Prediction 3b and Theory 3. The regression results suggest that futures prices move four to five times more than we would expect from the basis simply converging to zero. To provide some economic context, the standard deviation of the annualized basis is on the order of 90 basis points in global equity markets, meaning that a one standard deviation increase in the basis corresponds to a 3.5 to 4.5 percentage decrease in annualized futures returns.

The next two rows report regression coefficients for the two sub-samples, which show similar results, implying similar return predictability even though the differences in the magnitude and variation of bases is very different in the two sub-samples. In the 2000-2007 sample, coefficients range from -2.9 to -4.8 depending upon the fixed effect specification, with t-statistics less than -3 in

[15] We report OLS results in the internet appendix Table A.4.

all specifications. In the 2007-2017 sub-sample, the coefficients range from -4.73 (when including time fixed effects in the regressions) to -5.58 (with entity fixed effects). To interpret the regression coefficients, we note that the average cross-sectional standard deviation of the basis is 111 basis points in the 2000-2007 sample, while it is 76 basis points in the 2007-2017 sample, indicating that the return predictability corresponding to a one standard deviation difference in the basis is similar across the two sub-samples.

The coefficients being significantly less than -1 indicate that the basis predicts returns in the spot market *in the same direction* as the futures market, in addition to predicting the convergence of futures prices towards spot prices. To test this implication directly, the last four columns of the first row report results with spot returns as the dependent variable. Consistent with the conjecture that the basis also predicts spot market returns in the same direction, the regression coefficients are all negative. Moreover, the negative coefficients from the spot market regressions are not as large in magnitude as those for futures returns. These results are consistent with Prediction 3b, where we find reliable estimates that $c < -1, \gamma > 0$, and $c < \gamma$, consistent with the basis containing information about uninformed leverage demand that impacts arbitrageuer financing rates.

Panel B of Table 2 reports results for the same regressions in currency markets. In the full sample regressions, the futures market regression coefficients range from -11.3 (with time and entity fixed effects) to -27.0 (with no fixed effects), suggesting that currency forward return predictability is 11 to 27 times greater in magnitude than basis convergence. The t-statistics indicate significance at the 5% level, except for the specification with time and entity fixed effects (t-stat = -1.76). Over the full sample, the cross-sectional standard deviation is 15 basis points, so the full-sample regression coefficient suggests that a one standard deviation increase in the basis corresponds to a decrease of 1.6 to 6.2 percent in annualized futures returns.

Looking at the last four columns of Panel B, we also see strong negative predictability for spot returns from the currency basis. We find that $c < -1, \gamma > 0$, and $c < \gamma$, consistent with Prediction 3b and the basis conveying information about uninformed leverage demand. These results also reject theories 1 and 2, who imply futures and spot return predictability from the basis should be of opposite sign. The results also contradict Prediction 3a that the basis reflects informed demand, which implies positive, not negative, predictability.

Given the substantial differences in the size of cross-currency bases across the sub-samples (see Table 1), there is also variation in the regression coefficients in the sub-samples. In the 1989-1999 sample, the futures market regression coefficients range from approximately -1 (with no fixed effects), to -3.36 (with time and entity fixed-effects), although t-statistics are weak. Given the standard deviation of the basis in the early sub-sample is on the order of 15 to 20 basis points, the point estimates suggest that a one standard deviation increase in the basis corresponds with approximately 20 to 50 basis points lower annualized futures returns. In the 2000-2007 sample, the regression coefficients range from -35.6 (with time and entity fixed effects) to -87.2 (with entity fixed effects). Since the standard deviation of the basis in this period is only 5 basis points, these results indicate that a one standard deviation increase in the basis corresponds with a decrease in annualized returns of about 2 to 4 percent. In the sample from July 2007 to December 2017, the regression coefficients range from -11.1 to -17.57. The standard deviation of the basis is on the order of 16 to 19 bps in this sub-sample, so a one standard deviation increase in the basis corresponds to a 2 to 3.5 percent decrease in annualized returns. Taken together, the currency results suggest that the return predictability of cross-currency bases for currency markets has been stronger in the sample since 2000. More importantly, the sign of the coefficients for futures and spot returns are consistently negative, with the coefficient for futures returns consistently more negative than it is for spot returns ($c < \gamma$) and with $c < -1$ for almost all specifications and subperiods. These results are consistent with Prediction 3b.

In both equity index and currency markets, the basis has time-series and cross-sectional return predictability for futures *and* spot markets, even over the period preceding the global financial crisis. Our results show that bases negatively predict returns in futures markets and spot markets in the same direction, in addition to simply converging to zero, consistent with the theory that demand-supply imbalances in leveraged asset exposure impact financing rates. In the next section, we study leverage demand directly by looking at investor and dealer positions to better understand the source of uninformed demand contributing to the basis and its return predictability.

3 Why Do Bases Predict Returns? – Linking Leverage Demand to Bases

The results from the previous section suggest that uninformed leverage demand in global equity and currency markets increases financing costs intermediaries face to provide leverage, resulting in bases between futures and spot prices. The return predictability reflects compensation to liquidity providers for holding economic exposures opposite leverage demand. In this section, we attempt to corroborate the link between the basis, intermediary financing costs, and end-user demand for leveraged asset exposure.

3.1 Equity Index Futures-Spot Basis and Investor Positioning

We start with equity index futures and examine the relationship between the futures-spot basis and demand for leveraged equity using data on investor positioning in US futures markets. For financial futures traded on US exchanges, the CFTC publishes the Traders in Financial Futures (TFF) report every Thursday, providing the aggregate long and short positions of investors categorized into four groups: Dealers/Intermediaries, Institutional, Levered Funds, and Other Reportables.[16]

For equity index i and investor category c, we define net positioning as:

$$\text{Net Positioning}_{i,c} = \frac{\text{Long Positions}_{i,c} - \text{Short Positions}_{i,c}}{\text{Open Interest}_i}. \tag{8}$$

This signed measure captures whether investors in a given category are net long or short in aggregate, and scales their net positioning by the open interest.[17]

Most trading in equity index futures occurs on exchanges, as opposed to over-the-counter. Hence, net positioning from the TFF report should capture a substantial amount of the overall positioning of investors in equity index derivatives. For our sample, we have data on positioning for futures traded on the S&P500, S&P400, DJIA, Russell 2000, and NASDAQ indices.

Fig. 2 plots the time-series of each of the positioning series for each equity index. With the exception of the Russell 2000, Dealer/Intermediary positioning is on average net negative over the sample period, while Institutional and Hedge Fund positioning is net positive (the opposite

[16]The report officially designates the category "Leveraged Funds", but we will use the term "Hedge Funds" interchangeably to refer to this category. These designations come from Form 40 filings completed by reportable traders, as mandated by the CFTC. The CFTC expounds on these designations, describing Dealers/Intermediaries as participants that "tend to have matched books or offset their risk across markets and clients... These include large banks (U.S. and non-U.S.) and dealers in securities, swaps, and other derivatives." The Institutional Asset Manager designation includes "pension funds, endowments, insurance companies, mutual funds, and portfolio/investment managers whose clients are predominantly institutional," while Hedge Funds are described as including "hedge funds and various types of money managers, including registered commodity trading advisors (CTAs); registered commodity pool operators (CPOs) or unregistered funds identified by the CFTC." The "Other" category includes traders who "mostly are using markets to hedge business risk, whether that risk is related to foreign exchange, equities, or interest rates."

[17]We construct our net positioning variables following the approach of Brunnermeier et al. (2008) and Moskowitz et al. (2012), who construct net positioning variables using the CFTC Commitments of Traders report, a similar report to the one we use that groups traders into more coarse categories.

holds for the Russell 2000 in the sample). For each index, dealers hold the largest net positions by magnitude, which are negatively correlated with those of all other investor categories.

Table 3 reports the correlations of net positioning across investor categories. Panel A reports the average correlation of net positioning by investor type *within* each index. For example, the entry in the Dealer Column and Institutional row represents the correlation of net positioning of Dealers and Institutional Investors calculated for each index and then averaged across the indexes. The average within-index correlation of Dealer and Institutional Investor net positioning is -0.66. Similarly, the average correlation of Dealer and Hedge Fund net positioning is -0.68, and the average correlation of Dealer and Other Investor net positioning is -0.28. The strong negative relationship between Dealer positioning and positioning of other types of investors is consistent with Dealers taking the other side of futures demand to provide leverage to end-users in equity markets.[18]

Panel B of Table 3 reports the average pairwise correlation of net positioning by investor type *across* indices. For example, the entry in the Dealer row and Dealer column corresponds to the average pairwise correlation of net positioning of Dealers in one index with Dealer positions in the other indices, averaged across all indices. Dealer positioning is, on average, 0.37 correlated across indices. For other investors, positioning is likewise positively correlated across indices with the strongest correlation for Hedge Funds (0.39). Taken together, the results from Panels A and B of Table 3 indicate that Dealer and end-user positions are strongly negatively correlated for a given index, and that positions by investor type are positively correlated across equity indices.

We next test whether futures positioning of dealers and other investors is related to the basis. We run a panel regression of futures-spot bases on dealer net positioning. Table 4 reports the results. There is a strong negative relationship between dealer net positioning and the basis. The coefficient on dealer positioning (which is scaled to mean zero and unit variance) is strongly significant, with a t-stat of -3.74 (column (1)). Adding entity, time, and entity and time fixed effects reduces the coefficient, but still yields a strong and significant negative relationship. This negative relationship holds in both the time-series and the cross-section. For a given futures contract, the basis declines as dealer net positioning increases, and across indices the basis is smaller when dealer net positions are larger. The results suggest that a one standard deviation increase in dealer

[18]The negative correlations need not imply that dealers are expanding their balance sheets to provide futures exposure to end-users. If end-users demand to purchase assets held by dealers, then dealers may reduce their balance sheets while meeting end-user demand. However, combined with the evidence of the persistent opposing signs of dealer and end-user positioning, the results suggest that dealers are taking on futures inventory to meet end-user demand, and the amount of inventory they take depends upon the amount of futures exposure demanded by end-users.

positioning corresponds to a 28.9 basis point decrease in the basis. Including time and entity fixed effects, the effect is a 10 basis point drop. In times and indices where dealers have substantial long (short) positions, the basis is more (less) negative. These findings are consistent with intermediation costs playing a role in determining bases. The size of the dealer's exposure increases its cost and risk of providing leverage, resulting in a bigger wedge between futures and spot prices.

We next investigate the relationship between end-user positioning and the futures-spot basis. We run multivariate regressions of the futures-spot basis on net positioning by Institutional investors, Hedge Funds, and Other investors. The last four columns of Table 4 report the results. Across all specifications, Institutional investor positioning is significantly positively related to the futures-spot basis. A one standard deviation change in institutional investor positioning leads to a 6.7 to 20.6 basis point increase in the futures-spot basis, depending on the fixed effects specification. Hedge Fund positioning is also positively related to bases, as are other investor positions, though the coefficients for other investors are smaller.

Overall, Table 4 shows that investor positioning captures substantial variation in futures-spot bases, explaining 26% of the variation over time and across markets without any controls and 69% of the variation in combination with time and entity fixed effects. The basis is strongly negatively correlated with dealer positioning in futures, and strongly positively correlated with end-user positioning in futures, consistent with the basis increasing with the amount of leverage demand being intermediated by dealers.

The return predictability results from the previous section are consistent with the leverage demand embedded in the basis being uninformed. The results in this section suggest that the source of uninformed demand in equity index futures appears to be coming from institutional investors and hedge funds. Although institutional investors and especially hedge funds are typically thought of as informed investors, and evidence seems to support that notion on average, our results do not dispute that claim. Rather, all we are saying is that institutional investors and hedge fund positions specifically in equity index futures may be uninformed. In other words, the information advantage these investors enjoy is likely manifested in other trades besides general market equity indices. One explanation of institutional investor and hedge fund uninformed demand in this market is that index futures provide a convenient (and cheap) vehicle to increase or decrease the equity beta of a portfolio. For example, institutional investors may trade in equity index futures for reasons primarily related to rebalancing the amount of equity risk in their portfolios, rather than for information-based reasons. A similar story may apply for hedge funds, who may need to rebalance their equity beta due to inflows or outflows. Anecdotal evidence suggests that the equity index futures market is often used for these purposes, which is consistent with the investor net positioning results we document. In addition, the equity index market is large, liquid, and highly informationally efficient, making it difficult to profit from informed trading or conversely cheap for uninformed trading (due to low adverse selection).

3.2 Equity Index Futures-Spot Basis and Dealer Financing Costs

To further investigate the impact of leverage demand via futures and its relation to dealer financing costs, we examine securities lending markets. Dealers in futures markets seek to maintain hedged positions that are not exposed to market risk. Hence, if a dealer takes on inventory to meet demand for long equity exposure in futures markets, they may hedge their exposure by purchasing shares in the underlying spot market. Dealers often obtain financing in order to hedge their futures exposure by lending out shares from their hedge positions in exchange for cash (see Figure 1). Securities lending is a cheaper financing strategy for most dealers than other types of borrowing, such as uncollateralized borrowing, since dealers can deduct a security lending fee from the rate they pay to borrow cash (Omprakash (2014); Song (2016)). As a result, dealer financing costs for an index should vary with the difficulty and cost of borrowing shares in the underlying asset. An implication of this mechanism is that if dealer financing costs are embedded in the pricing of futures, then the futures-spot basis should be related to security lending fees and utilization.

To test this implication we use the Markit Securities Finance (MSF) Buy Side Institutional dataset, which contains daily data on stock loans aggregated from a variety of market participants from August 2004 to 2019. The dataset contains information on security lending utilization, a measure of the ease of borrowing a stock, which is defined as the ratio of the value of shares on loan from beneficial owners to the value of the inventory of shares available to be lent out by beneficial owners. From May 2007 onwards, the MSF dataset also provides data on the security lending fee for stocks. Both variables provide a proxy for the marginal cost of borrowing shares, which is directly related to the financing costs that dealers pay to finance their hedge positions.

We combine stock-level security lending data from MSF with the index weights of individual constituents in each index to create an index-weighted average of borrowing costs for each index. We windsorize the data at the 1st and 99th percentiles in order to avoid the impact of potential data errors. When security lending information is not available for a particular stock, we exclude that stock from our index-level calculations and re-normalize the index weight for each stock that has available data. This approach is equivalent to assuming that the stock with missing data has the same value as the index-weighted average of all stocks with available data in the index.

The MSF dataset has good coverage for the universe of stocks we study. In 2004, the beginning of the sample, we cover at least 80% of the index for 14 of the 18 indices we study, and cover at least 80% for all of the indices in our sample by 2008. Table A.10 in the internet appendix summarizes information on data coverage for the MSF data across the indices in our sample.

We test the relationship between the basis and security lending measures by running regressions of year-on-year changes in the futures spot-basis on year-on-year changes in each of the security lending measures, with standard errors clustered by entity and time. We use the Hansen-Hodrick correction to adjust standard errors for overlapping observations.[19] Panel A of Table 5 reports the results. The coefficient on security lending utilization is significantly negative and indicates that a 10% increase in security lending utilization corresponds to a decrease of 19 to 29 basis points in the basis, depending on the regression specification. The last four columns of Panel A repeat the regressions using lending fees as the independent variable. The coefficient on security lending fees is significant at the one percent level across all specifications, where a one percent increase in the stock lending fee corresponds to a 29 to 35 basis point decline in the futures-spot basis.

This evidence suggests an economically significant relationship between the basis and security lending costs. Moreover, the evidence is also consistent with the basis increasing in end-user demand for long-equity exposure that is not offset by corresponding demand for short-equity exposure. There are two potential mechanisms at play, both of which might be happening simultaneously, that are consistent with our story. The first mechanism is that dealers are increasing the supply of shares available to borrow in the cash-equity market when faced with demand for futures, where the increased supply reduces security lending utilization and fees and increases the basis. The second potential mechanism is that there is a negative relationship between the basis and shorting demand in the cash equity market. A primary purpose of the equity security lending market is to facilitate shorting. High demand to short, by borrowing shares in the underlying, re-

[19] We run these regressions in changes rather than levels due to potential non-stationarity in the security lending measures. Furthermore, we use year-on-year changes rather than changes over other horizons (such as weekly changes or monthly changes), to mitigate the impact of seasonal covariation between securities lending and equity demand that we find in the data that can confound inference (e.g., for nearly all of the indices in our sample, returns and security lending utilization and fees spike during dividend season). We obtain similar results by deseasonalizing and detrending the security lending variables and the basis.

duces financing costs to meet long demand in the futures market for dealers, resulting in a smaller basis. For both potential mechanisms, the basis is increasing in end-user demand for long-equity exposure that is not offset by corresponding demand for short-equity exposure.

Finally, we examine how index level security lending utilization and fees are related to dealer net positioning in futures, to come back full circle to the results in the previous subsections. Panel B of Table 5 reports results from regressing net futures positioning changes on security lending utilization and fees. There is a positive relationship between dealer positioning and securities lending measures, consistent with the theory. Point estimates range from 3.2 to 8.3, depending upon the fixed effects included, and indicate that a 10 percent change in security lending utilization corresponds to a 0.32 to 0.81 standard deviation change in dealer net positioning. Coefficient estimates on security lending fees are also significantly positive across all specifications, and indicate that a one percent increase in an index's security lending fee corresponds to a 0.46 to 0.63 standard deviation increase in dealer net positioning.

The evidence in equity futures markets contextualizes the supply and demand factors that lead to the emergence of bases. Dealers provide leverage to meet demand for leveraged equity exposure by end-users, taking the opposite side of their demand in futures markets, and hedging their positions in cash equity markets. The futures-spot basis reflects the financing cost in excess of benchmark borrowing rates that dealers face to hedge their equity exposure, which is affected by demand pressure from investors in futures markets and securities lending costs. Dealers who provide liquidity by taking the other side of leverage demand require compensation, which shows up in bases having negative return predictability for futures and spot market returns. We next identify and test a similar explanation for the basis in currency markets.

3.3 Covered Interest Rate Parity Violations and Currency Hedging Demand

We analyze covered interest rate parity violations in currency markets, using the same lens to understand supply and demand forces for the currency basis. Du et al. (2018) argue that cross-currency bases are related to intermediary financing costs, demonstrating a relationship between cross-currency bases, intermediary positions, and various financing spreads. We focus on the relationship between covered interest rate parity violations and demand for leveraged currency exposure coming from currency hedging demand.

We construct two proxies for investor currency hedging demand. The first is Net International

Investment Positioning (Net IIP), constructed across G10 countries from December 1989 to December 2017 using data from the IMF (annual frequency). Net IIP is defined as the financial assets of residents of an economy that are claims on non-residents and gold bullion held as reserve assets minus the liabilities of residents of an economy to non-residents. Net IIP incorporates the financial assets and liabilities of both the public and the private sector of an economy. Positive Net IIP indicates that the foreign investments of residents exceed the domestic investments of non-residents. Net IIP provides information about potential currency hedging demand by investors. In markets where there are many foreign investors with domestic investments (a negative Net IIP), we expect foreign investors to hedge their currency exposure by selling the local currency and buying their home currency through derivatives markets. Conversely, when residents are heavily invested abroad (a positive Net IIP), they will hedge their currency exposure by selling foreign currencies and purchasing the local currency. This currency hedging motive predicts that currencies of economies with a positive (negative) Net IIP have strong buying (selling) demand in currency derivatives markets, resulting in a more (less) positive basis. We test these predictions using Net IIP data, where we normalize Net IIP by country GDP (from Datastream). Since Net IIP is also available back to 1989, we explore the relationship between Net IIP and cross-currency bases in the pre-financial crisis period as well.

The second measure of currency hedging demand we consider is institutional investor positions in currency futures from the Traders in Financial Futures report published by the CFTC.[20] The Chicago Mercantile Exchange lists futures of currency crosses of seven G10 currencies against the USD: the Australian Dollar, the Euro, the Canadian Dollar, the Japanese Yen, the New Zealand Dollar, the Swiss Franc, and the British Pound Sterling. As before, we define net positioning via equation (8). Positive net positioning indicates that institutional investors hold a net long futures position in a currency versus the US dollar. Because a substantial portion of currency derivatives trading occurs over-the-counter, this measure only captures a portion of overall currency derivatives positioning of institutional investors, although these positions are likely correlated to investor behavior in forwards and swap markets, too.

Figure 3 displays scatter plots of the time-series average of Net IIP and Institutional Investor

[20] Borio et al. (2016) and Sushko et al. (2017) present evidence that hedging demand from foreign banks and institutional investors may play a role in cross-currency bases. The CFTC futures report also provides futures positions for dealers and intermediaries, which may or may not capture hedging demand from foreign banks. However, the futures positions of dealers and intermediaries appear to most strongly negatively correspond with the positions of hedge funds. We analyze the relationship between the basis and other futures investors' positions in the internet appendix.

positioning, both proxies for hedging demand, versus the the cross-currency basis, over the January 2008 to December 2017 sample period. The scatter plots show a positive cross-sectional relationship between bases and currency hedging demand. In particular, negative cross-currency bases are associated with lower hedging demand (most notably for investment, or high local interest rate, currencies such as the Australian and New Zealand Dollar), and positive cross-currency bases are associated with more positive hedging demand for funding currencies. Those familiar with the carry trade (that goes long investment currencies and short funding currencies) will recognize a connection between the basis and the currency carry strategy, which we investigate in more detail below and find commonality in the return predictability generated from the basis and carry.

More formally, we regress the cross-currency bases on the hedging proxies, including controls for local interbank lending rates (which Du et al. (2018) find are related to the basis) and the local LIBOR-OIS spread, which proxies for local bank funding conditions. The independent variables are normalized to zero mean and unit standard deviation. Standard errors are clustered by entity and time. Table 6 reports the results, which show that institutional investor positioning is significantly positively related to the basis, with a coefficient of 6 bps. The coefficient drops to 2.9 bps when controlling for local nominal interest rates and LIBOR-OIS spreads, and becomes an insignificant (though still positive) 1.8 bps when also adding entity fixed effects. The coefficient on Net IIP is 12.1 in a univariate regression with time-fixed effects, but increases to 15.8 when controlling for local interbank rates and LIBOR-OIS spreads. However, the coefficient on Net IIP falls sharply and is insignificant when including time and entity fixed effects, though given the degrees of freedom in this specification the power is very low and time and entity fixed effects soak up most of the variation in cross-currency bases. Coefficients on local interbank lending rates are mixed, but LIBOR-OIS spreads are consistently positive and significant.

These results suggest that currency hedging proxies have substantial explanatory power for cross-sectional variation in the cross-currency bases. Their ability to explain time-series variation in the cross-currency basis is more limited, as evidenced by the much weaker results when entity fixed effects are included. Libor-OIS spreads, however, which capture information about local bank funding conditions, have substantial explanatory power for both the time-series and cross-section of cross-currency bases. Both sets of results are consistent with our story of leverage demand interacting with intermediary financing costs that determine the basis.

Given the longer time-series of data available on Net IIP, we can also analyze the cross-currency basis before the financial crisis. Figure 4 plots the average standardized cross-currency basis from

January 1990 to December 2006 versus the average Net IIP for G10 countries. Given the heterogeneity in the magnitude of cross-currency bases over time we documented earlier, we standardize observations by subtracting the cross-sectional mean and dividing by the cross-sectional standard deviation at each point in time. The basis and Net IIP are positively related (with the Swiss Franc being an outlier, possibly related to the outsized role of Switzerland's international banking sector relative to the size of its economy, particularly in the early 1990s). Fig. 4 also plots the average annualized basis against the average Net IIP value (in billions of US dollars) for each economy, and plots the average annualized cross-currency basis against Net IIP normalized by total value of assets held by banks within each economy (obtained from BIS). Both plots show a strong positive cross-sectional relationship between the cross-currency basis and Net IIP, even when bases are small before the crisis. This result suggests that bases reflect more than just financing costs in excess of benchmark borrowing rates, which are tiny in the pre-crisis era, and capture information about leverage demand for currencies.

The return predictability of cross-currency bases from the previous section suggests that investors holding positions opposite currency hedging demand earn compensation from doing so. The mechanism is not necessarily that currency hedging demand directly drives cross-sectional exchange rate predictability. For example, Gabaix and Maggiori (2015) argue that economies where foreign investors disproportionately hold domestic assets have higher expected currency returns, since financiers with limited risk-bearing capacity must take on currency risk to intermediate the flow of international capital. In this setting, cross-currency bases (and currency hedging demand) exhibit cross-sectional exchange-rate predictability *because* they capture information about foreign holdings of domestic assets.

3.4 Further Evidence of Demand Effects in the Basis

We provide two demand-based stories for the return predictability in global equity and currency markets. In equity markets, we hypothesize that uninformed demand pressure for equity market exposure creates return predictability through short-term liquidity provision to compensate intermediary dealers. In currency markets, the basis also represents uninformed (hedging) demand, but the return predictability stems more from longer-horizon risk compensation of currencies with significant foreign capital flows. We investigate these two related explanations further.

We start by examining the contemporaneous relationship between the basis and market returns.

We run a panel regression of monthly changes in the 5-day rolling average of the basis in each market on monthly returns in that market.[21] Price pressure from short-term liquidity demand should generate a positive contemporaneous relation between the basis and returns (and a negative predictive relation, which we have shown). Table 7 reports the results. In global equities, we find a positive and significant contemporaneous relationship between the basis and returns. A positive return of one percent in a month corresponds with a 2.8 to 3.5 basis point increase in the basis. In currency markets, however, the relationship between changes in the basis and returns is statistically and economically insignificant. This result suggests that short-term price pressure due to liquidity demand is not driving currency bases, which is perhaps consistent with longer-term risk compensation driving the return predictability in currencies.

Another testable implication of the short-term price/liquidity pressure in equity bases and longer-term risk compensation in currency bases is to examine the persistence of the basis. Fig. 5 plots an autocorrelation function of the daily basis in global equities and currencies. The basis appears to be much more persistent in currencies. For global equities, the basis has positive autocorrelation up to 90 days. For currencies, the basis is significantly positively autocorrelated for more than a year. These results suggest the presence of a more persistent driver of the basis in currencies, where leverage demand is more persistent than it is in global equity index futures markets. The difference in the persistence of demand across the two contexts is consistent with the two sources of return premia we conjecture – a shorter-term liquidity premium to compensate liquidity providers in equities (Kyle (1985); Grossman and Miller (1988)) and a longer-term risk premium to compensate investors willing to hold riskier currencies (e.g., those more affected by foreign capital flows, as suggested by Gabaix and Maggiori (2015)).

4 Implications for Implied Interest Rates from Derivatives

Our results that the basis is partly related to leverage demand in futures markets also has implications for recent work that studies interest rates implied from derivative prices. For example, Binsbergen et al. (2019) extract the risk-free rates implied by SPX and DJIA equity index options and compare them to US Treasury yields to study the behavior of the Treasury "convenience yield," since the former does not reflect the money-like liquidity benefits that make Treasury securities "convenient." The equity index futures we study are closely related to the equity index

[21] We obtain similar results using the current basis, though the 5-day moving average reduces noise in the estimates.

options Binsbergen et al. (2019) extract interest rates from, so it is interesting to examine our results through this complementary lens.

The futures-spot basis is the difference between interest rates embedded in futures prices and interbank lending rates. One issue with extracting implied interest rates from futures is estimating expected dividends, which introduces error. In addition, we focus primarily on futures contracts with less than three months maturity due to limited data on dividend estimates, while Binsbergen et al. (2019) use options with longer maturities in order to study the term structure of convenience yields. Since nearly all trading happens in the closest to expiration contract, the type of leverage demand pressure we identify might not be present in longer maturity contracts. Of course, it is also the case that convenience yields should be especially present for short-maturity safe assets, too, so understanding interest rates implied in shorter maturity derivatives prices is interesting.[22]

With these caveats in mind, we recast our results in terms of understanding interest rates embedded in futures prices. First, consider the results relating the basis to futures positioning from Table 4, which provide some quantitative guidance on how much leverage demand can affect futures-implied interest rates. We find that a one standard deviation increase in the futures positions of dealers corresponds with a ten basis point decrease in the basis, which equivalently corresponds to a 10 basis point decrease in the implied interest rate in futures. Taking the estimates from Binsbergen et al. (2019), who compare option-implied interest rates to matched-maturity Treasury yields, our results suggest that maybe 10 to 20 bps may be coming from demand shocks (depending on their size). These effects are small, but not inconsequential. These results also suggest that when interpreting the behavior of derivatives-implied interest rates in event-study contexts, it might also be important to understand how those events might impact leverage demand for risky assets.

Second, the demand channel can also explain some of the cross-sectional heterogeneity in bases we observe within a given market. For example, the large variation in bases across U.S. equity indices in Table A.1 is difficult to justify purely from differences in marginal investor funding rates (Theory 2 from Section 2), but may be accommodated by a combination of varying leverage demand and intermediary costs. Consider the basis in Russell 2000 futures, which provides an interesting, albeit extreme, case. Table A.1 shows that the basis for Russell 2000 futures is, on average, -76 basis points, suggesting that the interest rate embedded in its futures are consistently

[22] In equilibrium, the supply of, and demand for, leverage can be related to the convenience yield (e.g., in the model of Diamond (forthcoming)). The leverage demand we study could very well be related to the Treasury convenience yield, but this potential relationship is outside the scope of our paper.

far lower than interbank lending rates. The futures positioning and securities lending data for the Russell 2000 suggest potential reasons for this large negative basis. Russell 2000 stocks, which are small-cap, are difficult to borrow and have high security lending fees (on average 64 bps, which is the highest among the equity indices in our sample). Hedge funds engaged in small-cap equity strategies might have persistent demand for short positions in R2000 futures, if they are a more convenient/cheaper vehicle to hedge their long positions than short-selling individual names. This demand for short futures exposure would result in a negative futures-spot basis. Another story consistent with these observations is that high security lending fees make it particularly cheap for dealers to provide long leverage in futures on the R2000, which also results in a negative basis. In both cases, R2000 futures illustrate an example where leverage demand and dealer provision of leverage can substantially change the interest rates embedded in risky assets.

Finally, we directly back out the interest rates implied by S&P 500 futures prices to compare them to Binsbergen et al. (2019). The internet appendix Table A.14 details the calculations and shows that we find similar values as Binsbergen et al. (2019) for 3-month interest rates extracted from options. We also report the same statistics for 6- and 12-month SPX box-spread implied interest rates, obtained from Jules van Binsbergen's website. We find that the implied interest rates from futures and from options are highly, but not perfectly, correlated (see appendix Table A.15). We also find that dealer futures positions are highly negatively correlated to the implied interest rates as well, especially at short horizons (3 month maturities), but less so at longer horizons. This evidence is consistent with the implied interest rates being related to dealer inventories of futures responding to short-term liquidity demand in equities.

Further understanding the similarities between futures- and option-implied interest rates, and their behavior across maturities, is beyond the scope of this paper, but is an interesting avenue for future research. Our results highlight that demand pressures can materially affect derivatives prices and the interest rates they imply, consistent with other results in other settings (e.g. Bollen and Whaley (2004); Garleanu et al. (2009); Constantinides and Lian (2015); Chen et al. (2018) and Borio et al. (2016)), providing complimentary evidence that expands the economic interpretation of implied interest rates obtained from derivative prices.

5 Leverage Demand Factor

Finally, we construct trading strategies to better quantify the return predictability of the basis and to study its relationship with other known return predictors in these markets.

5.1 Cross-Sectional LMH Leverage Demand Factor

We construct a Low-Minus-High (LMH) Leverage Demand trading strategy within an asset class that goes long futures that are priced "cheap" relative to spot market prices and short futures that are priced "expensive" relative to spot market prices. Unlike the conventional basis trade, which trades futures versus their underlying assets, this strategy only trades in futures versus other futures. Positive returns to the strategy suggest that markets where futures are trading cheap relative to their fair values outperform markets where futures are trading expensive relative to their fair values.

We follow Koijen et al. (2018) and form portfolios of futures weighted in proportion to the cross-sectional rank of their futures-spot basis. Specifically, we form portfolios at the end of each month, with the weight on each security i at time t given by

$$w_t^i = \kappa_t \left(\text{rank}\left(-X_t^i\right) - \frac{N_t + 1}{2} \right) \tag{9}$$

$$R_{\text{LD,t}} = \sum_{i=1}^{N_t} w_t^i \tilde{r}_{i,t} \tag{10}$$

where N_t is the number of available securities at time t, and the scalar κ_t ensures that the sum of the long and short positions equals 1 and -1, respectively. X_t^i is asset i's basis, lagged one-day, and $R_{LD,t}$ is the return at time t of the LMH Leverage Demand portfolio. This is similar to the weighting scheme employed by Asness et al. (2013), who show that the resulting portfolios are highly correlated with other zero-cost portfolios that use different weights.[23]

Analogous to the approach of Koijen et al. (2018) in calculating the carry of the carry trade portfolio, we construct a measure of the basis profitability of each LMH Leverage Demand portfo-

[23] Given that five out of the eighteen equity indices in our sample are US indices, we test the robustness of our results by constructing an alternative global equity LMH Leverage Demand portfolio excluding all US indices except the S&P500, and an additional alternative portfolio excluding all US indices. The resulting portfolios are highly correlated with our baseline specification and realize similar performance. The results are reported in the internet appendix A.4.

lio as the expected profitability of the basis converging to zero in each futures contract,

$$BP_t^{portfolio} = -\sum_i w_t^i B_t^i. \tag{11}$$

Comparing the returns in equation (11) to the returns in equation (10) identifies whether returns are driven purely by futures converging to spot prices. If the returns to the LMH Leverage Demand portfolio exceed the basis profitability, then the basis must also negatively forecast returns in the spot market in addition to capturing basis profitability.

5.2 Time-Series LMH Leverage Demand Factor

To study the time-series return predictability of the basis, we construct a timing strategy within each asset class as follows, where the weight of security i is given by

$$w_{i,t} = z_t \left(-2\mathbb{I}\left(X_{i,t} - \bar{X} > 0\right) - 1\right),$$

and where $\mathbb{I}(X_t^i - \bar{X} > 0)$ is an indicator function that equals one if $X_t^i > \bar{X}$ and X_i^t is the basis of asset i. As before, we set z_t so that we have 2 dollars of exposure in each period, though instead of being \$1 long and \$1 short at all times, the strategy will typically take either aggregate long or short positions.

5.3 LMH Leverage Demand Returns

Table 8 reports the annualized mean, standard deviation, skewness, excess kurtosis, and Sharpe ratio of the returns of the cross-sectional LMH portfolio ("LMH Leverage Demand XS") and the timing strategy ("LMH Leverage Demand TS").

For comparison, we report the same statistics for other known predictors of the cross-section and time-series of returns in global equities and currencies: value and momentum (from Asness et al. (2013), updated from the AQR Data library), time-series momentum (from Moskowitz et al. (2012), updated from the AQR Data Library) and carry (from Koijen et al. (2018), updated from Ralph Koijen's website). The table also reports the same statistics for the excess returns to a passive long position equally weighting each instrument within an asset class, rebalanced monthly. The passive long strategy in currencies holds an equal weighted long position in a basket of currencies versus the US dollar.

The annualized Sharpe ratio of the cross-sectional LMH portfolio is 0.83 in global equities and 0.57 in currencies, while the annualized Sharpe ratio of the timing portfolio is 0.38 in global equities and 0.43 in currencies. A combination of equity and currency basis portfolios, which weights them inversely by their in-sample volatilities, has a Sharpe ratio of 1.11 for the cross-sectional strategies and 0.61 for the timing strategies, indicating low correlation of returns between the equity and currency strategies (correlation of -0.11 for the cross-sectional strategies and -0.01 for the timing strategies). Within each asset class, the performance of the cross-sectional strategy is of similar magnitude to the performance of the carry trade, and is slightly higher than that of the standalone value and momentum strategies. Other well-known predictors of asset returns in these markets, particularly carry and momentum, exhibit strong negative skewness, as documented by Brunnermeier et al. (2008) and Daniel and Moskowitz (2016). We find no evidence of negative skewness or excess kurtosis for the LMH Leverage Demand strategies in either asset class.

5.3.1 Basis Profitability

To further understand the profitability of these strategies, we decompose their returns into the component coming from basis convergence in futures markets and the component coming from spot predictability. For any futures contract, the basis must converge to zero at expiration, and hence part of the returns come from this convergence. If the basis does not predict spot market returns, then all of the returns come from futures and spot prices converging.

Fig. 6 plots the cumulative returns of the cross-sectional equity and currency LMH Leverage Demand portfolios against their basis profitability. For equities, returns are about 3.8 times larger than the basis profitability of the portfolio. For currencies, the returns to the currency LMH portfolio exceed the portfolio's basis profitability by more than 15 times. Moreover, the profitability of the currency LMH strategy is particularly notable before the Global Financial Crisis, where covered interest rate parity violations are small (and hence basis convergence is small), yet the returns to the currency LMH strategy are substantial. The currency LMH strategy earns an average annualized return of 3.8% from February 1989 to June 2007, while it earns an average annualized return of 3.5% from July 2007 to December 2017. Conversely, basis convergence contributes only an average annualized return of 24 basis points in the 1989-2007 sample, and an average annualized return of 40 basis points in the 2007-2017 sample. In both periods, the majority of the profitability of the LMH strategy does not come from basis profitability, but rather predictability of the underlying spot market. The trading strategies are exploiting the return predictability we documented in Table 2 – the basis negatively predicts spot market returns, in addition to the convergence of futures and spot prices. The magnitude of the return predictability is large, generating an annualized Sharpe ratio of 1.11 when combined across equity and currency markets.

5.3.2 Spanning Tests and Factor Exposures

Table 9 reports regression results of the LMH factors on the other known return factors (value, momentum, carry, time-series momentum, and passive long). The cross-sectional global equity LMH portfolio loads positively on the momentum portfolio (t-statistic of 2.86), but insignificantly on the other factors. The strategy earns an alpha of 43 basis points per month (t-stat of 3.02), with an annualized information ratio (alpha divided by residual volatility) of 0.75. In the second column of the table, the global equity LMH timing portfolio has a positive loading on the momentum portfolio (t-statistic of 3.22) and the passive long portfolio (t-statistic of 3.01), and has a negative loading on the time-series momentum portfolio (t-statistic of -5.22). The strategy earns an alpha of 93 basis points per month (t-statistic of 2.84), with an annualized information ratio of 0.71.

The returns of the cross-sectional currency LMH portfolio in the third column of Table 9 load significantly positively on the returns of the currency carry portfolio, with a coefficient of 0.49 (t-stat of 12.07), and significantly negatively on the returns to a portfolio that is passively long foreign currencies versus the US dollar, with a coefficient of -0.26 (t-stat of -6.90).[24] The portfolio earns a monthly alpha of 12 basis points per month (t-statistic of 1.46) and an annualized information ratio of 0.28. The returns of the currency LMH timing portfolio, in the fourth column, load significantly positively on the carry portfolio, with a coefficient of 0.60 (t-statistic of 7.92), significantly negatively on the passive long portfolio, with a coefficient of -0.89 (t-statistic of -12.56), and moderately positively on the currency time-series momentum portfolio, with a coefficient of 0.07 (t-statistic of 1.71). The timing portfolio earns an alpha of 27 basis points per month, which is significant at the 10% level, corresponding with an information ratio of 0.32.

The strongest relationship we find is between the currency LMH Leverage Demand strategy and the currency carry strategy, which we study in more depth in the internet appendix. The evidence suggests that the currency LMH and carry portfolio load on a common factor. Given the relationship between interest rates and the flow of international capital, the relationship between

[24]For the currency LMH portfolio, we obtain similar results by replacing the carry and passive long factors with the carry trade and dollar risk factors from Lustig et al. (2011). Results are reported in the internet appendix Table A.16.

the currency carry and LMH leverage demand strategies is intuitive. However, the currency LMH strategy earns much of its alpha when the carry portfolio crashes, perhaps suggesting that while a portion of the returns of the carry trade may be compensation for crash risk (Brunnermeier et al. (2008)), a more substantial portion may be compensation for common risk (e.g., Lustig and Verdelhan (2007, 2009); Jurek (2014) and Bekaert and Panayotov (2019)).

Combining the equity and currency portfolios for every factor on both the left hand side and right hand side of the regression (with each asset class portfolio weighted inversely by its in-sample volatility), the combined cross-sectional LMH Leverage Demand portfolio's returns load significantly on the combined carry factor, with a coefficient of 0.19 (t-stat of 3.20), significantly on the combined momentum portfolio, with a coefficient of 0.22 (t-stat of 3.31), and moderately negatively on the combined time-series momentum portfolio, with a coefficient of -0.04 (t-statistic of -1.85). The combined cross-sectional LMH portfolio earns an alpha of 36 basis points per month (t-stat of 4.05), with an annualized information ratio of 1.04. The combined LMH timing portfolio loads significantly on the combined momentum portfolio, with a coefficient of 0.35 (t-statistic of 2.38) and significantly negatively on the combined time-series momentum portfolio, with a coefficient of -0.14 (t-statistic of -2.78) and the passive long portfolio, with a coefficient of -0.24 (t-statistic of -2.93). The combined timing portfolio earns a monthly alpha of 60 basis points per month (t-statistic of 3.05), and information ratio of 0.78. Jointly, these results suggest that the LMH portfolios have some exposure to other factors known to predict returns, namely carry and momentum, but that these factors cannot fully explain the returns from bases and leverage demand.

5.3.3 Liquidity and Volatility

If the return premium associated with the basis is driven by uninformed liquidity demand and financial intermediary lending costs, then the premium may vary with measures of liquidity, intermediation costs, and volatility. We consider the intermediary capital ratio factor of He et al. (2017), the non-traded innovations to market liquidity from Pástor and Stambaugh (2003), the monthly innovations of the Treasury Minus Eurodollar (TED) spread, and the monthly level and changes in the VIX. All variables are signed such that a positive sign corresponds with higher liquidity and lower volatility (and are standard normalized for ease of interpretation).

Table 10 presents the results of time-series regressions of the cross-sectional LMH factor returns on the liquidity and volatility measures. The cross-sectional currency LMH strategy loads positively and significantly on the TED spread, suggesting that a one-standard deviation increase in the TED spread decreases returns by 27 basis points. This result indicates that the currency LMH strategy is exposed to fluctuations in funding liquidity, which is consistent with currency exposure associated with international capital flows being exposed to the financing conditions of the financiers that facilitate those flows (e.g. Gabaix and Maggiori (2015)). The combined strategy loads significantly on the VIX, where a one-standard deviation increase in the VIX corresponds to a 16 basis point increase in returns. This result is consistent with the insight from Nagel (2012) that the returns to liquidity-provision strategies are high during periods of high volatility, due to the withdrawal of liquidity supply during these periods. The alphas for both the global equity and currency LMH Leverage Demand strategies remain positive and significant when controlling for exposure to the liquidity and volatility variables.

We also explore the relationship between currency hedging demand and financing costs, which we argue is the source of the return predictability of cross-currency bases, and the LMH Leverage Demand factor in currencies. Using the detailed net IIP and institutional positioning data, as well as interbank lending rates and Libor-OIS spreads, we form five portfolios following equation (9), using each of these five variables to sort currencies. Specifically, we go long high interest rate currencies and short low interest rate currencies, short currencies with more buying demand in futures markets and long currencies with more selling demand, and short currencies with high LIBOR-OIS spreads and long currencies with low LIBOR-OIS spreads. We regress the returns to the LMH portfolio on the returns of these portfolios over the period from January 2008 to December 2017, when Traders in Financial Futures Report data is available.

Table 11 reports the results from these regressions. The alpha of the basis factor remains at 28 to 32 basis points in univariate regressions on portfolios sorted by Institutional Investor Positioning, Libor-OIS spreads, and local interbank lending rates. The alpha drops to 22 basis points per month when regressed on the returns to a portfolio that sorts currencies on their corresponding Net IIP values, with the LMH portfolio loading significantly on the Net IIP portfolio (t-stat of 8.20). In a multivariate regression that includes all of the portfolios as regressors, the alpha of the LMH portfolio drops to 9 basis points per month (Information Ratio of 0.23), with significant positive loadings on portfolios sorted on Net IIP (t-stat of 9.98) and Libor-OIS (t-stat of 2.84). The evidence suggests that a substantial amount of the return predictability of cross-currency bases during this time period can be explained by exchange rate returns associated with international capital flows and returns associated with local bank funding conditions, consistent with our story. Moreover, since Net IIP is only measured at an annual frequency, it is possible that higher frequency position data could better capture currency hedging demand or international capital flows that would explain even more of the returns of the currency LMH portfolio.

6 Conclusion

We show that violations of the law of one price convey more than just intermediation costs, offering information about demand for leveraged asset exposure. Consistent with this notion, we find that bases between futures and spot prices predict returns in futures and spot markets *in the same direction*, distinct from futures market and spot market prices merely converging, and do so negatively. These results are consistent with uninformed leverage demand driving part of the basis that increases asset-specific financing costs facing intermediaries. Investigating the source of this demand in each market, we find that leverage demand in equity markets appears related to short-term price pressure for directional equity exposure, where the return premium we document from the basis represents compensation to liquidity providers holding economic exposures opposite leverage demand. In currency markets, the demand for leverage emanates from currency hedging demand, related to the flow of capital in international markets, where the return premium associated with the basis represents compensation to investors willing to hold riskier currencies. In both markets, the basis reflects information about both intermediary financing costs and leverage demand that predicts expected returns in the underlying market. Our results highlight the important role that supply and demand imbalances play in giving rise to violations of the law of one price.

Tables and Figures

Figure 1: **Mechanics of Futures Trading**

The figure illustrates the mechanics of market making in equity index futures. Dealers in the futures market meet demand for leveraged equity exposure from end-users by selling futures contracts to the end-users. They hedge their exposure to equity market fluctuations by buying stocks in the underlying cash equity market. Dealers obtain financing for their hedge positions by lending out their cash equity shares or entering into repurchase agreements for those shares, both of which provide a cheaper source of financing than uncollateralized borrowing (see Omprakash (2014) and Song (2016) for more discussion).

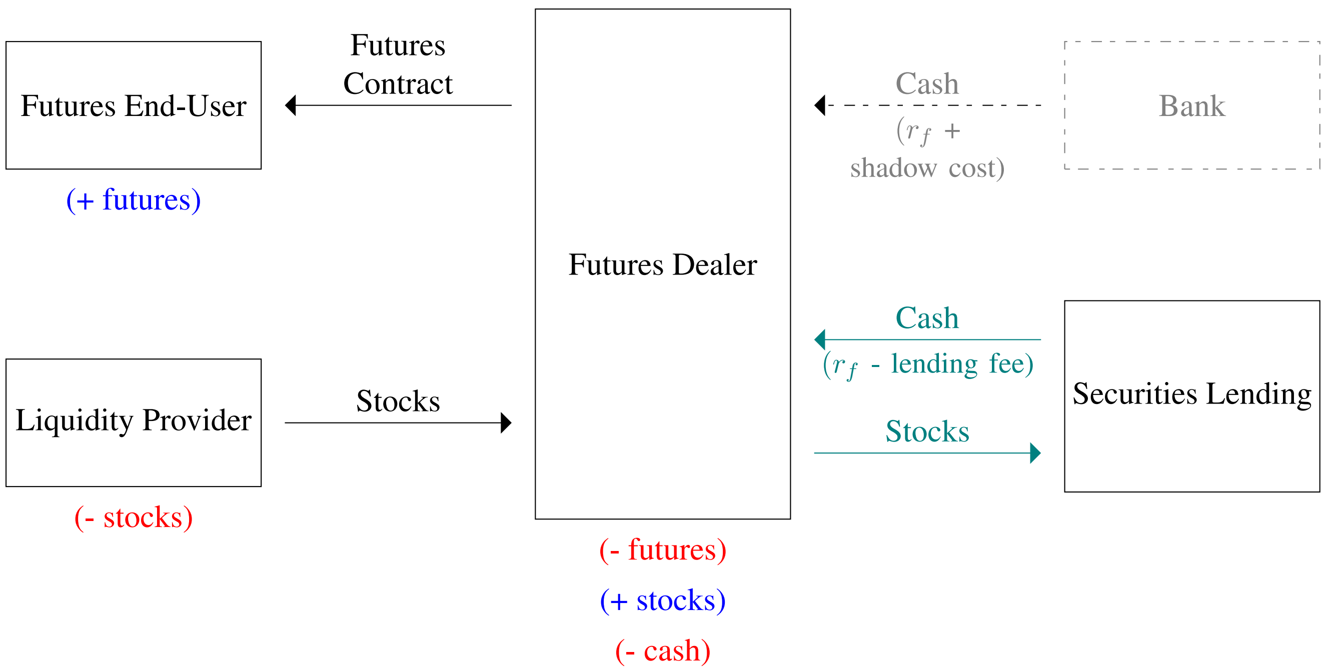


Figure 2: **Net Positioning from Traders in Financial Futures Report**

The plots graph the ratio of the net number of contracts held by each investor type to the total open interest for a given equity index, as published in the weekly Traders in Financial Futures Report published by the CFTC. The report has been published in real time from 2010 to 2017, with the CFTC back-filling values from 2006 to 2010.

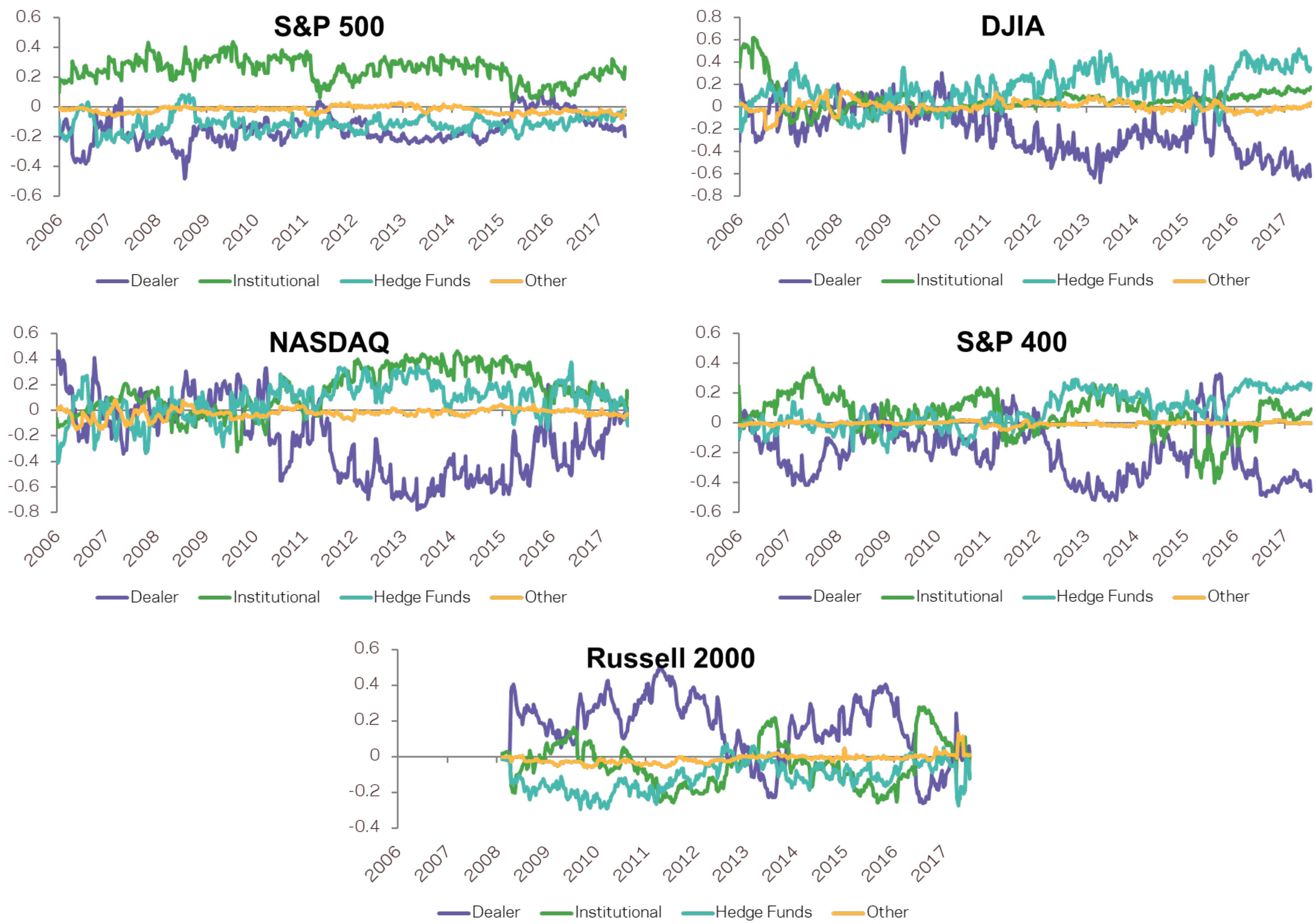


Figure 3: **The Cross-Currency Basis and Hedging Demand: 01/2008-12/2017**

The figure displays scatter plots of the time-series average from January 2008 to December 2017 of each of our three currency hedging measures (Net IIP, Dealer Futures Positioning, and Institutional Investor Futures Positioning) against the time-series average of the cross-currency basis from January 2008 to December 2017, for each currency in which data is available for both the hedging measure and the cross-currency basis. Each scatter plot also includes the line of best fit from regressing each currency hedging measure on the cross-currency basis.

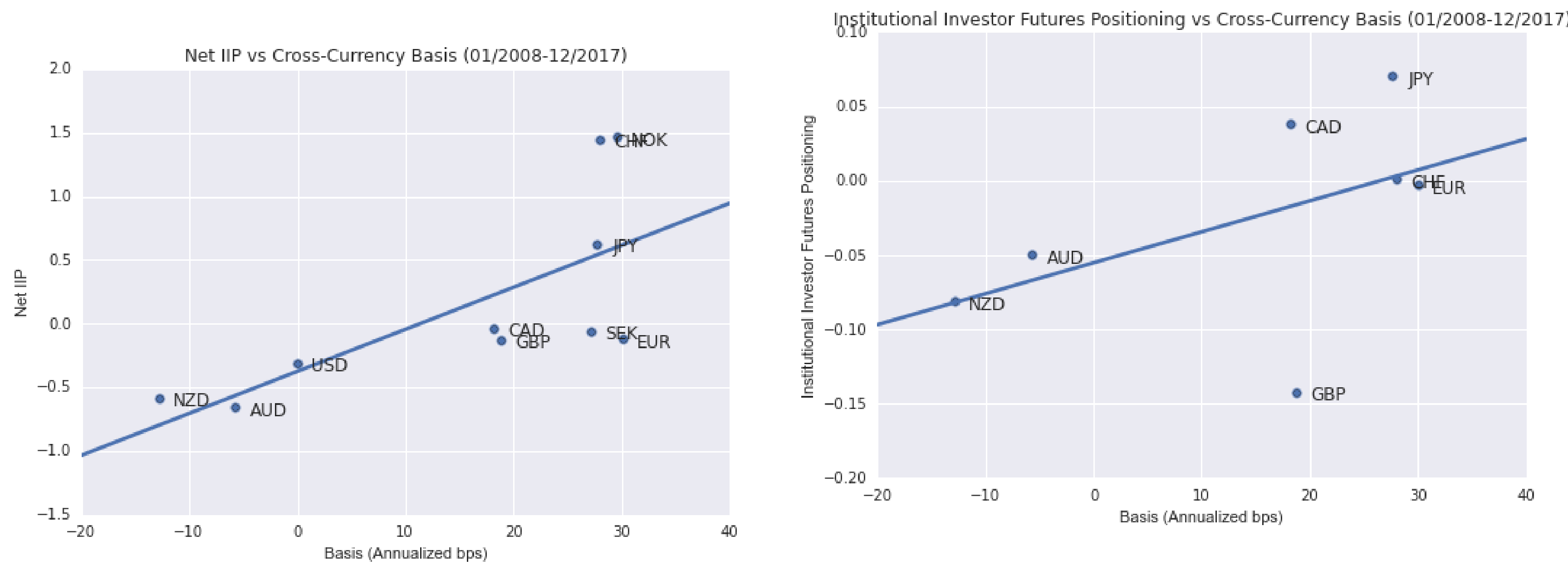
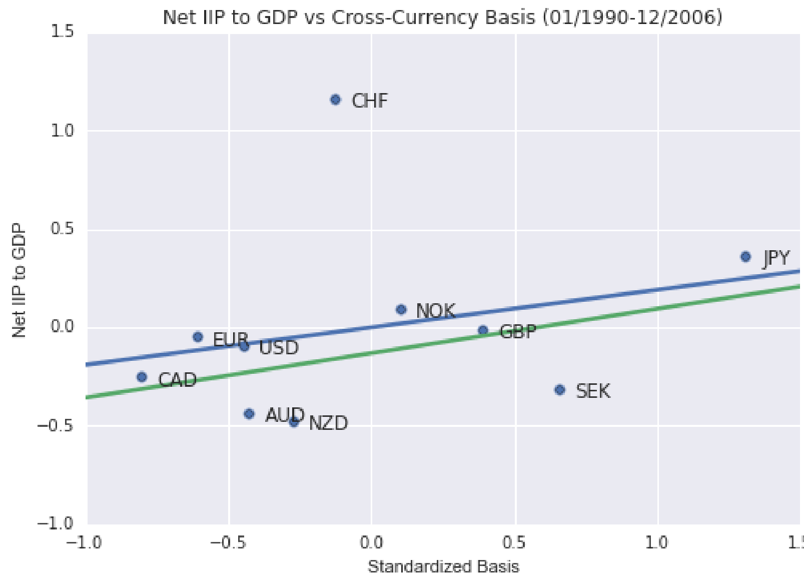
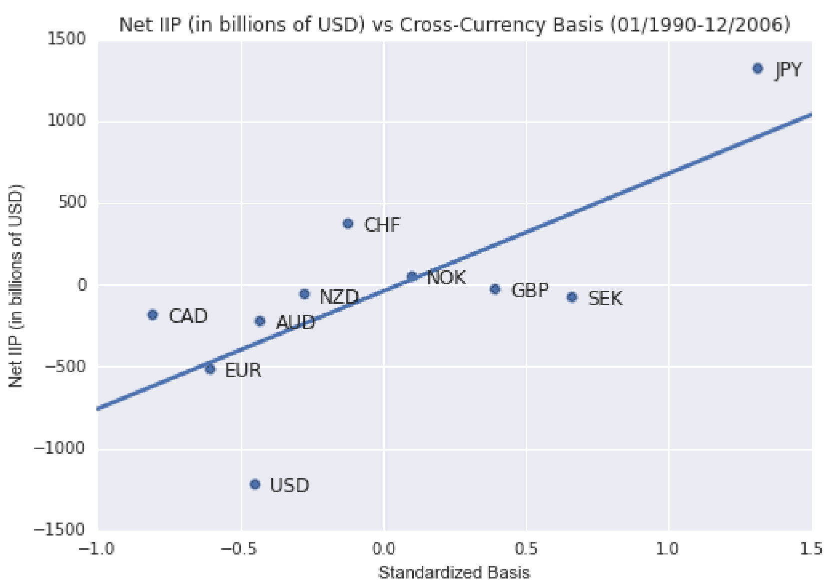


Figure 4: **The Cross-Currency Basis and Hedging Demand: 01/1990-12/2006**

The figure displays scatter plots of the time-series average from January 1990 to December 2006 of Net International Investment Positioning (Net IIP) values against the time-series average of the standardized cross-currency basis from January 1990 to December 2006, for each currency in which data is available for both the hedging measure and the cross-currency basis. There are three plots: the first plots Net IIP, in billions of US dollars, against the cross-currency basis, the second plots the ratio of Net IIP to local GDP against the cross-currency basis, and the third plots the ratio of Net IIP to total assets in the banking system against Net IIP. Each scatter plot also includes the line of best fit from regressing each currency hedging measure on the cross-currency basis. The plot of Net IIP to local GDP against the cross-currency basis also includes the line of best fit excluding the Swiss Franc from the regression. The standardized cross-currency basis is calculated by subtracting the cross-sectional mean from each observation and dividing by the cross-sectional standard deviation at teach point in time.





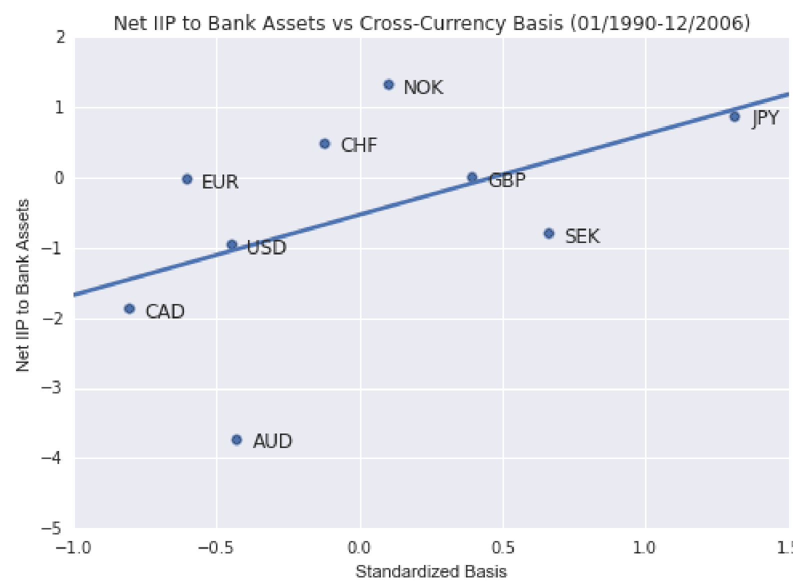


Figure 5: **Autocorrelations of the Basis**

The figure plots the autocorrelation function of the basis for multiple lags. Panel A plots the autocorrelation function of the basis in global equity markets, estimated from January 2000 through December 2017. Panel B plots the autocorrelation function of the basis in currency markets, estimated from January 2008 through December 2017. The values are calculated via a univariate panel regression of the basis on lagged values of the basis, including entity-fixed effects. Standard errors are clustered by index and time. The dotted lines represent the 95% confidence interval for the autocorrelation coefficients.

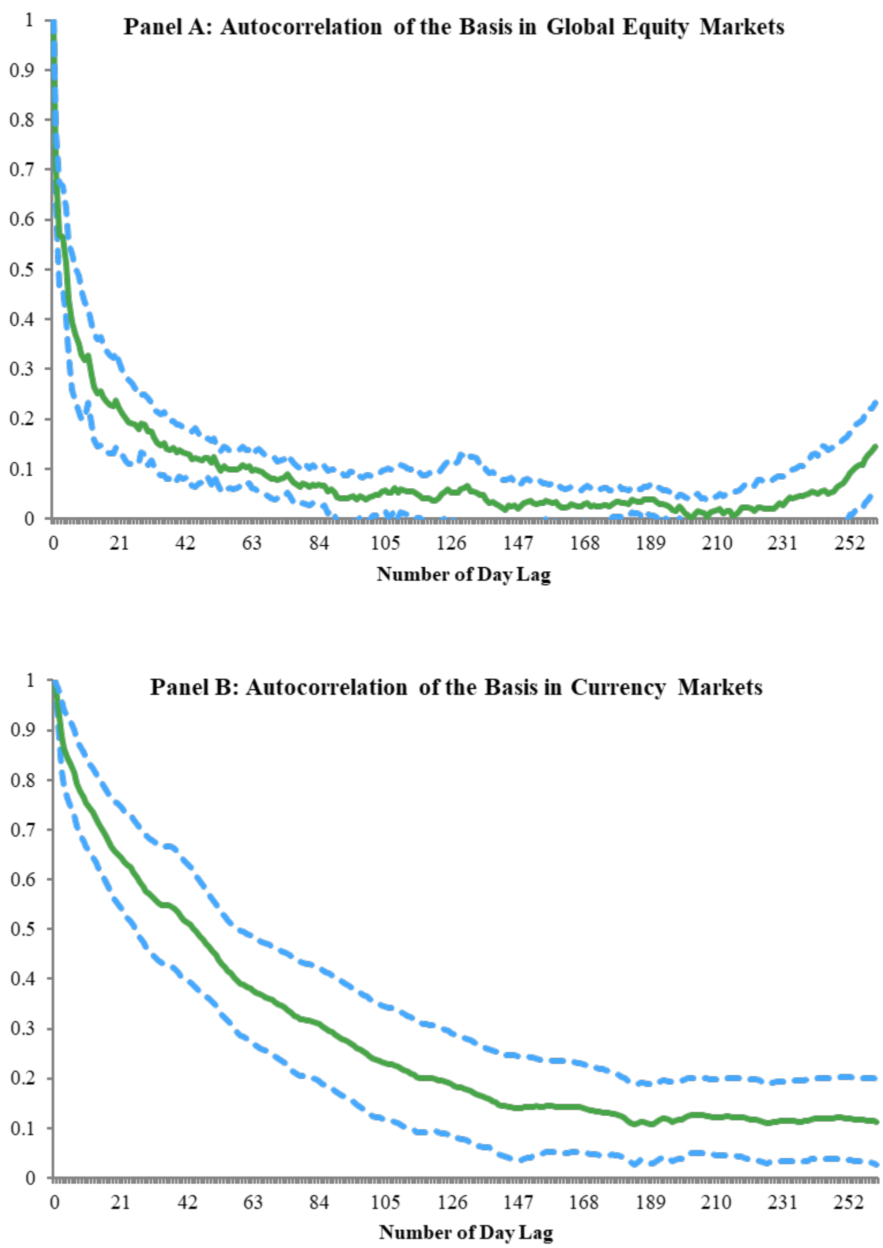
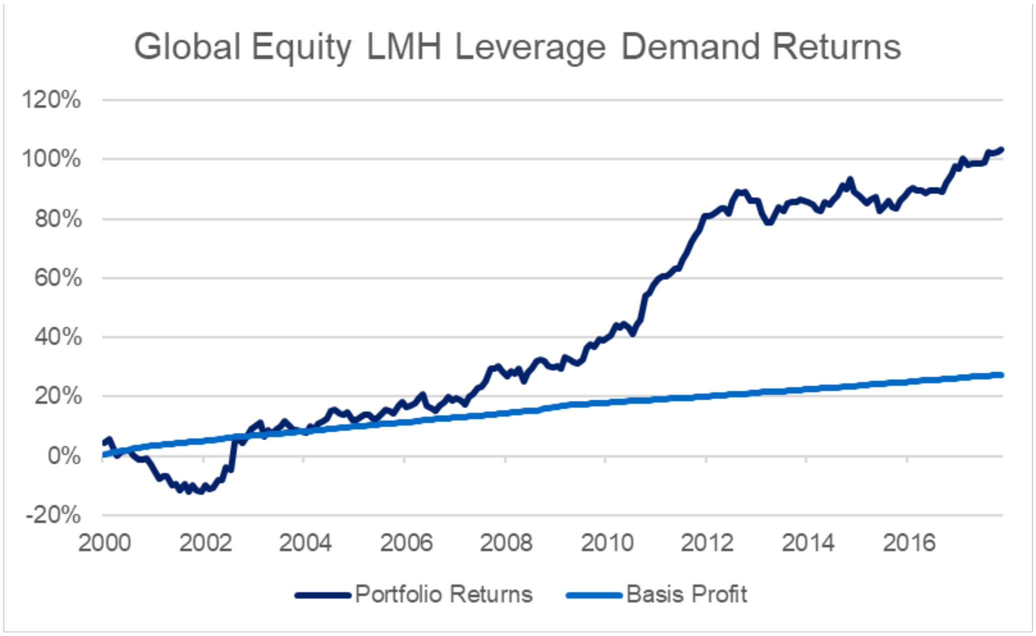


Figure 6: **LMH Leverage Demand Strategy Returns Versus Basis Profitability**

The figure plots the cumulative returns of the currency and equity LMH Leverage Demand strategies against the basis profitability of each respective strategy. The basis profitability of each strategy is the expected return on the LMH Leverage Demand portfolio assuming that spot prices do not change and that futures converge to their underlying spot values.



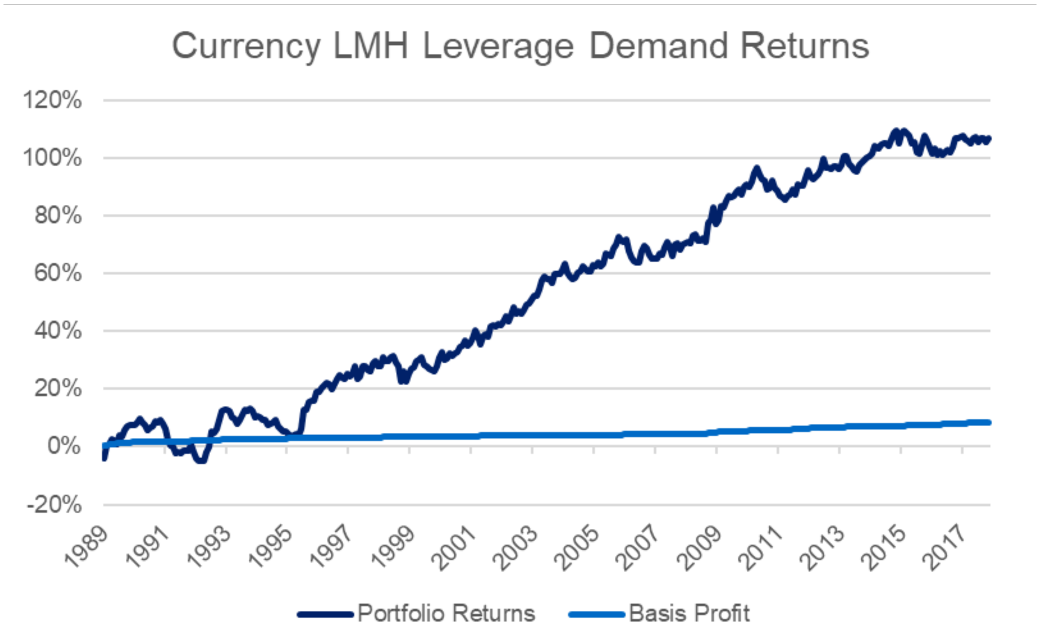


Table 1: **Basis Summary Statistics**

The table displays summary statistics of the annualized basis in currency and global equity markets. For each asset class, the table displays the average value of all basis observations within the sample, the average absolute value of all basis values within the sample, the average of the time-series standard deviation of the basis for each asset in the sample, and the average of the cross-sectional standard deviation of the basis in each time period. The table displays these statistics over the full sample, as well as in sub-samples of the data.

		Average Basis	Average Absolute Basis	Average Basis TS-Stdev	Average Basis XS-Stdev
Global Equities	Jan. 2000-Dec. 2017	-0.83	56.58	91.84	90.39
	Jan. 2000-Jun. 2007	-8.15	63.92	94.48	111.05
	Jul. 2007-Dec. 2017	3.52	52.22	84.82	75.67
Currencies	Jan. 1989-Dec. 2017	6.91	13.37	22.90	15.14
	Jan. 1989-Dec. 1999	0.06	11.89	24.95	17.89
	Jan. 2000-Jun. 2007	2.51	4.85	4.87	5.04
	Jul. 2007-Dec. 2017	15.06	19.71	16.51	18.83

Table 2: **Basis Return Predictability**

The table reports the results from a set of panel regressions of the form

$$r^{fut}_{i,t+1} = a_i + b_t + cBasis_{i,t} + \epsilon_{i,t+1}$$

$$r^{spot}_{i,t+1} = \alpha_i + b_t + \gamma Basis_{i,t} + \eta_{i,t+1}$$

where r^i_{t+1} is the return of asset i, a^i is the asset-specific intercept (or fixed effect), b_t are time-fixed effects, $Basis^i_t$ is the futures-spot basis in market i measured in the previous period, and c is the coefficient of interest that measures the return predictability coming from the basis. Panel A reports the results for regressions for a panel of global equities. Panel B reports the results for regressions for our panel of currencies. In each panel, the numbers in the first four columns correspond with regressions where the dependent variable is futures returns for a given market. The numbers in the second four columns correspond with regressions where the dependent variable is the spot return for a given market. The basis is scaled to be a weekly rate, so a coefficient of -1 indicates that subsequent returns in a market move one-for-one in the opposite direction of the basis. Each panel reports regression results for the full sample as well as for sub-samples of the data. The full-sample regressions are run using weighted least squares, where each observation is weighted by the inverse of the variance of the basis of its sub-sample. Observations are sampled weekly. Standard errors are clustered by time and entity. t-statistics are reported in parentheses.

Panel A: Global Equities

Dependent variable =	Futures Market Returns, c				Spot Market Returns, γ			
Jan. 2000-Dec. 2017	-5.18	-4.08	-5.18	-4.05	-3.63	-2.46	-3.56	-2.33
	(-2.63)	(-3.73)	(-2.46)	(-3.67)	(-1.92)	(-1.97)	(-1.75)	(-1.81)
Jan. 2000-Jun. 2007	-4.75	-3.08	-4.58	-2.89	-3.30	-1.64	-3.08	-1.39
	(-4.15)	(-3.33)	(-3.97)	(-3.07)	(-2.88)	(-1.78)	(-2.64)	(-1.47)
Jul. 2007-Dec. 2017	-5.52	-4.75	-5.58	-4.73	-3.93	-3.00	-3.90	-2.86
	(-1.70)	(-2.66)	(-1.59)	(-2.57)	(-1.25)	(-1.45)	(-1.14)	(-1.30)
Time FE	No	Yes	No	Yes	No	Yes	No	Yes
Entity FE	No	No	Yes	Yes	No	No	Yes	Yes

Panel B: Currencies

Dependent variable =	Futures Market Returns, c				Spot Market Returns, γ			
Jan. 1989-Dec. 2017	-27.00	-17.08	-24.35	-11.32	-26.15	-16.17	-23.48	-10.37
	(-2.72)	(-2.74)	(-2.34)	(-1.76)	(-2.64)	(-2.61)	(-2.26)	(-1.60)
Jan. 1989-Dec. 1999	-1.00	-3.18	-0.97	-3.36	-0.45	-2.52	-0.43	-2.71
	(-0.59)	(-1.28)	(-0.57)	(-1.35)	(-0.28)	(-1.03)	(-0.27)	(-1.10)
Jan. 2000-Jun. 2007	-82.07	-46.48	-87.24	-35.64	-81.38	-45.67	-86.48	-34.64
	(-4.17)	(-3.89)	(-3.16)	(-1.41)	(-4.12)	(-3.80)	(-3.12)	(-1.35)
Jul. 2007-Dec. 2017	-13.81	-11.10	-17.57	-14.51	-12.65	-9.89	-16.31	-13.09
	(-1.91)	(-2.75)	(-1.37)	(-2.80)	(-1.75)	(-2.48)	(-1.26)	(-2.56)
Time FE	No	Yes	No	Yes	No	Yes	No	Yes
Entity FE	No	No	Yes	Yes	No	No	Yes	Yes

Table 3: **Correlation of Net Positioning by Investor Type**

Net positioning is the ratio of the net number of contracts held by each investor type to the total open interest for a given equity index, as published in the weekly Traders in Financial Futures Report published by the CFTC. Panel A reports the correlation of net positioning by each investor type with other investor types within a given index, averaged across indices. Each element of Panel A represents the average time-series correlation of net positioning across investor types for each index. Panel B reports the average correlation of net positioning for each investor type across indices. For example, the the Dealer/Dealer component of the table represents the average time-series correlation of net-positioning of dealers across each of the five indices.

Panel A: Correlation of Within-Index Net Positioning, Averaged Across Indices

	Dealer	Institutional	Hedge Funds	Other
Dealer	1.00	-0.66	-0.68	-0.28
Institutional		1.00	0.12	0.11
Hedge Funds			1.00	0.05
Other				1.00

Panel B: Correlation of Cross-Index Net Positioning, Averaged Across Indices

	Dealer	Institutional	Hedge Funds	Other
Dealer	0.36	-0.16	-0.40	-0.12
Institutional		0.11	0.21	0.10
Hedge Funds			0.39	0.08
Other				0.01

Table 4: **Regression of Futures-Spot Basis on Investor Net Positioning in Futures**

Net positioning is the ratio of the net number of contracts held by each investor type to the total open interest for a given equity index, as published in the weekly Traders in Financial Futures Report published by the CFTC. Panel A reports results of a regression of the futures-spot basis on standardized dealer net positioning. Panel B reports results of a regression of the futures-spot basis on standardized institutional, levered, and other positioning. Futures-spot basis is an annualized rate. Standard errors are clustered by index and time, with t-statistics in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dealer	-28.87**	-22.20**	-25.50**	-10.00**				
	(-3.74)	(-4.22)	(-3.26)	(-2.87)				
Institutional					20.63**	12.60**	18.00*	6.74***
					(3.11)	(3.99)	(2.73)	(6.24)
Hedge Funds					19.74**	18.64**	14.81*	3.82
					(3.68)	(4.10)	(2.57)	(0.73)
Other					1.11	1.03	7.16	5.41**
					(0.37)	(0.41)	(1.87)	(2.90)
R^2	0.26	0.32	0.62	0.69	0.27	0.32	0.62	0.70
Observations	2874	2874	2874	2874	2874	2874	2874	2874
Time FE	No	No	Yes	Yes	No	No	Yes	Yes
Entity FE	No	Yes	No	Yes	No	Yes	No	Yes

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

Table 5: **The Futures-Spot Basis, Securities Lending, and Futures Positions**

Panel A reports results from a set of univariate regressions of year-on-year changes of the futures-spot basis of an index on changes in security lending utilization and fees for that index. Observations are sampled monthly. Panel B reports a set of univariate regression results of year-on-year changes in dealer net positioning (standardized) on changes in security lending utilization and security lending fees. Observations are sampled weekly. Standard errors are clustered by index and time and are adjusted using the Hansen-Hodrick correction for overlapping observations, with t-statistics in parentheses. The reported R^2 values are within-group values that do not include variation explained by fixed effects.

Panel A: The Basis and Securities Lending								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
utilization	-2.830***	-2.882***	-1.856**	-1.908**				
	(-5.78)	(-6.42)	(-2.11)	(-2.23)				
fee					-0.289***	-0.286***	-0.347***	-0.343***
					(-4.99)	(-5.72)	(-3.02)	(-3.08)
R^2	0.0132	0.0136	0.00512	0.00535	0.00287	0.00282	0.00341	0.00335
Observations	2672	2672	2672	2672	2088	2088	2088	2088
Time FE	No	No	Yes	Yes	No	No	Yes	Yes
Entity FE	No	Yes	No	Yes	No	Yes	No	Yes

Panel B: Futures Positioning and Securities Lending								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
utilization	8.113**	8.261**	3.244	3.378				
	(2.23)	(2.18)	(1.10)	(1.23)				
fee					0.00465*	0.00463*	0.00618*	0.00625*
					(1.70)	(1.73)	(1.81)	(1.92)
R^2	0.0530	0.0539	0.00873	0.00924	0.00878	0.00872	0.0155	0.0160
Observations	2619	2619	2619	2619	2435	2435	2435	2435
Time FE	No	No	Yes	Yes	No	No	Yes	Yes
Entity FE	No	Yes	No	Yes	No	Yes	No	Yes

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

Table 6: **Cross-Currency Bases and Currency Hedging**

Reported are regression results for the annualized currency basis on proxies for currency hedging demand. The dependent variable is the difference between three-month forward rates and the IBOR-implied forward rate on local interbank lending rates. The Institutional variable is institutional investor positioning from the Traders in Financial Futures report, as defined in equation (8). Net IIP is the ratio of an economy's net international investment positioning to its GDP. LIBOR is the local interbank lending offer rate, and LIBOR-OIS is the difference between LIBOR and the Overnight Indexed Swap rate for a currency. Observations for the regressions on positioning variables are weekly from 2008 to 2017. Observations for the Net IIP regressions are annual observations from 2008 through 2017. Standard errors are clustered by entity and time, with t-statistics in parentheses.

	Dependent variable = cross-currency basis					
	(1)	(2)	(3)	(4)	(5)	(6)
Institutional	5.95**	2.87*	1.77			
	(2.79)	(2.00)	(1.11)			
LIBOR		-20.95***	6.92		-9.56	0.20
		(-7.16)	(1.70)		(-1.67)	(0.04)
LIBOR-OIS		12.44**	12.02**		25.35**	22.88**
		(2.59)	(3.08)		(3.33)	(2.79)
Net IIP				12.07**	15.79**	-14.50
				(3.25)	(2.84)	(-1.81)
R^2	0.26	0.58	0.74	0.27	0.49	0.69
Observations	3654.00	3654.00	3654.00	100.00	90.00	90.00
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Entity FE	No	No	Yes	No	No	Yes

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

Table 7: **Contemporaneous Relationship Between Basis and Market Returns**

The table reports results from a set of contemporaneous panel regressions of the five-day rolling average of the basis in each market on the excess returns of the market, including time and entity fixed effects. Panel A reports regression results for global equity index futures. Panel B reports regression results for currency forwards. Returns are in percentage points, while the basis is measured in annualized basis points, so the regression coefficients can be interpreted as the number of basis points the basis moves contemporaneously with a one percent return. Standard errors are clustered by entity and time, with t-statistics in parentheses.

	Panel A: Global Equities Basis			
	(1)	(2)	(3)	(4)
Market returns	2.827***	2.830***	3.493**	3.503**
	(2.91)	(2.90)	(2.31)	(2.31)
R^2	0.0285	0.0286	0.160	0.160
Observations	3509	3509	3509	3509
Time FE	No	No	Yes	Yes
Entity FE	No	Yes	No	Yes

	Panel B: Cross-Currency Basis			
	(1)	(2)	(3)	(4)
Market returns	-0.682	-0.682	-0.0767	-0.0744
	(-1.78)	(-1.78)	(-0.36)	(-0.35)
R^2	0.0194	0.0195	0.465	0.465
Observations	1080	1080	1080	1080
Time FE	No	No	Yes	Yes
Entity FE	No	Yes	No	Yes

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

Table 8: **LMH Leverage Demand Returns By Asset Class**

The table reports the mean annualized excess return, annualized standard deviation, skewness of monthly returns, kurtosis of monthly returns, and annualized Sharpe ratio of the LMH Leverage Demand strategy returns in global equities and currencies. The table displays statistics displays statistics corresponding with the cross-sectional LMH Leverage Demand portfolios ("LMH Leverage Demand XS") and the LMH Leverage Demand timing portfolios ("LMH Leverage Demand TS"). The table also reports statistics for strategies based on well known predictors of returns, Value, Momentum, Time-series Momentum and Carry, within each asset class, as well as statistics for a passive long portfolio of all assets within the asset class for comparison. The last panel reports these statistics for a diversified combination portfolio that combines each strategy in both equities and currencies, where each asset class is weighted by the inverse of its full-sample standard deviation of returns.

Asset Class	Strategy	Mean	Stdev	Skewness	Excess Kurtosis	Sharpe Ratio
Global Equities	**LMH Leverage Demand XS**	5.78	6.99	0.44	2.30	0.83
	LMH Leverage Demand TS	6.52	17.01	0.26	1.42	0.38
	Value	3.68	9.18	0.07	1.13	0.40
	Momentum	5.52	11.04	-0.27	1.43	0.50
	Carry	8.81	9.92	0.24	2.54	0.89
	TS-Momentum	19.94	27.09	-0.05	1.43	0.74
	Passive Long	6.62	14.89	-0.61	1.10	0.44
Currencies	**LMH Leverage Demand XS**	3.70	6.45	0.01	0.59	0.57
	LMH Leverage Demand TS	5.23	12.05	0.27	3.46	0.43
	Value	3.16	7.62	0.32	2.47	0.42
	Momentum	2.35	8.49	-0.49	1.08	0.28
	Carry	4.51	7.61	-0.62	1.41	0.59
	TS-Momentum	12.86	18.17	0.20	1.89	0.71
	Passive Long	1.11	8.03	-0.16	0.76	0.14
Diversified Combo	**LMH Leverage Demand XS**	4.98	4.47	0.21	1.52	1.11
	LMH Leverage Demand TS	5.88	9.57	0.24	1.06	0.61
	Value	3.27	5.95	-0.01	1.40	0.55
	Momentum	3.75	7.42	-0.36	1.05	0.51
	Carry	6.40	6.26	-0.30	1.38	1.02
	TS-Momentum	15.70	16.87	-0.01	1.07	0.93
	Passive Long	3.04	8.05	-0.46	2.10	0.38

Table 9: **LMH Leverage Demand Factor Exposure to Other Factors**

The table reports regression results for each LMH Leverage Demand portfolio's returns in currencies and equities on a set of other portfolio returns of factors that explain the cross-section of asset returns: the passive long portfolio returns (equal-weighted average of all securities), the value and momentum factors of Asness et al. (2013), the time-series momentum (TSMOM) factor of Moskowitz et al. (2012), and the carry factor of Koijen et al. (2018), each calculated separately asset-class by asset class and updated through the end of our sample. The combined strategy combines portfolios across equities and currencies, weighting the currency and equity portfolios inversely by their sample standard deviations. The returns are scaled to be in percentage points by multiplying by 100. The table reports intercepts or alphas (in percent) from regressing the LMH Leverage Demand strategy returns on the other factor returns, as well as the regresion coefficients or betas on the various factors. The last two rows report the R^2 from the regression and the information ratio, IR, which is the alpha divided by the residual volatility from the regression.

	Global Equities		Currencies		Combined	
	XS	TS	XS	TS	XS	TS
Value	0.00	-0.13	0.00	0.12	0.01	-0.01
	(0.07)	(-0.89)	(0.08)	(1.49)	(0.13)	(-0.09)
Momentum	0.18***	0.46***	0.06	0.04	0.22***	0.35**
	(2.86)	(3.22)	(1.09)	(0.37)	(3.31)	(2.38)
Carry	0.10	-0.27*	0.49***	0.60***	0.19***	0.15
	(1.58)	(-1.87)	(12.07)	(7.92)	(3.20)	(1.17)
TSMOM	-0.02	-0.24***	0.04*	0.07*	-0.04*	-0.14***
	(-1.00)	(-5.22)	(1.66)	(1.71)	(-1.85)	(-2.78)
PassiveLong	0.02	0.23***	-0.26***	-0.89***	-0.04	-0.24***
	(0.49)	(3.01)	(-6.90)	(-12.56)	(-0.99)	(-2.93)
α	0.43***	0.93***	0.12	0.27*	0.36***	0.60***
	(3.02)	(2.84)	(1.46)	(1.66)	(4.05)	(3.05)
R^2	0.06	0.16	0.35	0.37	0.14	0.10
IR	0.75	0.71	0.28	0.32	1.04	0.78

t-statistics in parentheses.

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

Table 10: **LMH Leverage Demand Strategies, Liquidity and Volatility**

The table reports the alphas and betas from a series of univariate regressions of the monthly returns of the cross-sectional global equity, currency, and combined LMH Leverage Demand strategies on measures related to liquidity provision. The measures include the intermediary capital ratio factor from He et al. (2017), the (non-traded) innovations to market liquidity from Pástor and Stambaugh (2003), the Treasury Minus Eurodollar (TED) Spread, the level of the VIX and changes in the VIX. Independent variables are signed such that positive numbers correspond to greater market liquidity and less market volatility. Returns in the regression are multiplied by 100, with t-statistics reported in parentheses.

		HKM	PS	TED Spread	VIX Change	VIX
Global Equities	Alpha	0.48	0.48	0.48	0.48	0.47
		(3.49)	(3.49)	(3.49)	(3.51)	(3.43)
	Beta	0.02	-0.11	-0.04	-0.17	-0.17
		(0.14)	(-0.78)	(-0.30)	(-1.31)	(-1.34)
Currencies	Alpha	0.31	0.31	0.31	0.30	0.30
		(3.08)	(3.08)	(3.10)	(2.94)	(2.94)
	Beta	0.01	0.03	0.27	0.13	-0.06
		(0.07)	(0.27)	(2.56)	(1.33)	(-0.64)
Diversified Combo	Alpha	0.42	0.41	0.42	0.41	0.41
		(4.71)	(4.71)	(4.73)	(4.70)	(4.63)
	Beta	0.02	-0.07	0.13	0.03	-0.16
		(0.21)	(-0.83)	(1.46)	(0.35)	(-1.97)

Table 11: **Currency LMH Leverage Demand Strategy Returns and Hedging Demand Proxies**

Reported are regression results for the returns to the currency LMH Leverage Demand portfolio on the returns to portfolios formed by sorting on three currency hedging demand proxies (Net IIP, institutional investor and dealer positions in currency futures), one portfolio that sorts on the local interbank lending rates corresponding with each currency, and one portfolio that sorts on the Libor-OIS rates corresponding with each currency. The Dealer and Institutional investor positioning come from the Traders in Financial Futures Report. Observations are monthly returns from 2008 to 2017. Coefficients are multiplied by 100, with t-statistics in parentheses. IR is the information ratio of the LMH Leverage Demand strategy with respect to each set of portfolios and equals the intercept from the regression divided by the residual standard deviation from the regression.

	Dependent variable = LMH Leverage Demand strategy returns					
α	0.31*	0.32*	0.28	0.31*	0.22	0.09
	(1.75)	(1.82)	(1.58)	(1.80)	(1.54)	(0.70)
Institutional		0.11				-0.22***
		(1.34)				(-2.78)
LiborOIS			0.15			0.25***
			(1.50)			(3.01)
SR				0.15**		-0.16*
				(2.22)		(-1.84)
IIP					0.65***	1.02***
					(8.20)	(9.98)
R^2	0.00	0.02	0.02	0.04	0.36	0.53
IR	0.55	0.58	0.50	0.57	0.49	0.23

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

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A Internet Appendix

A.1 Basis Summary Statistics

Table A.1: **Starting Dates for Basis Series**

Global Equities		Currencies	
Instrument	Starting Date	Instrument	Starting Date
AU	Jun-00	AU	Jan-89
BD	Jan-00	CN	Apr-92
CN	Jan-00	BD	Jan-89
DJIA	Apr-02	JP	Jan-89
ES	Jan-00	NZ	Sep-96
EUROSTOXX	Jun-01	NW	Jan-89
FR	Jan-00	SD	Jan-89
HK	Jan-00	SW	Jan-89
IT	Sep-04	UK	Jan-89
JP	Jan-00	US	Jan-89
NASDAQ	Jan-00		
NL	Oct-00		
SD	Jun-05		
SW	Jan-02		
UK	Jan-00		
US	Jan-00		
USRU2K	Dec-02		
USSPMC	Jan-02		

Table A.2: **Global Equities Basis Asset-level Summary Statistics**

For each asset in the sample of global equities, the table includes the average value of the basis in the sample, the average value of the absolute value of the basis in the sample, and the time-series standard deviation of the basis in the sample. The table reports statistics over the full sample, as well as over two sub-samples: one sub-sample from January 2000 to June 2007, and one-sub-sample from July 2007 to December 2017. The basis is reported in annualized terms in basis points.

	Jan. 2000-Dec. 2017			Jan. 2000-Jun. 2007			Jul. 2007-Dec.2017		
	Average Basis	Average Absolute Basis	Basis TS-Stdev	Average Basis	Average Absolute Basis	Basis TS-Stdev	Average Basis	Average Absolute Basis	Basis TS-Stdev
AU	-10	72	106	-48	107	133	13	51	77
BD	-2	32	57	-9	29	59	3	34	55
CN	-15	40	57	-30	47	61	-4	35	51
DJIA	10	21	27	7	15	23	12	23	29
ES	12	93	158	6	111	198	17	80	122
EUROSTOXX	10	35	57	13	32	64	8	37	53
FR	11	47	90	19	63	122	5	36	56
HK	-32	205	284	-38	242	325	-26	176	247
IT	11	43	61	-11	40	54	17	43	62
JP	-21	54	78	-38	64	92	-8	46	64
NASDAQ	1	28	41	-2	28	44	3	28	38
NL	20	51	180	27	46	59	16	54	225
SD	7	73	145	42	103	207	1	68	128
SW	46	62	102	14	39	62	63	74	114
UK	8	32	47	3	38	57	13	27	37
US	11	22	31	15	22	33	8	22	30
USRU2K	-76	88	86	-89	96	83	-70	85	87
USSPMC	-8	29	46	-9	17	24	-8	33	52

Table A.3: **Cross-Currency Basis Asset-level Summary Statistics**

For each asset in the sample of currencies, the table includes the average value of the basis in the sample, the average value of the absolute value of the basis in the sample, and the time-series standard deviation of the basis in the sample. The table reports statistics over the full sample, as well as over three sub-samples: one sub-sample from January 1989 to December 1999, one sub-sample from January 2000 to June 2007, and one-sub-sample from July 2007 to December 2017. The basis is reported in annualized terms in basis points.

	Jan. 1989-Dec. 2017			Jan. 1989-Dec. 1999			Jan. 2000-Jun. 2007			Jul. 2007-Dec.2017		
	Average Basis	Average Absolute Basis	Basis TS-Stdev	Average Basis	Average Absolute Basis	Basis TS-Stdev	Average Basis	Average Absolute Basis	Basis TS-Stdev	Average Basis	Average Absolute Basis	Basis TS-Stdev
AU	-7	11	29	-12	15	47	0	5	6	-7	10	12
CN	8	11	15	-3	5	7	-1	3	3	20	20	14
BD	10	14	21	-1	7	9	-1	4	4	27	28	24
JP	18	18	16	12	13	12	9	9	4	27	28	18
NZ	-6	11	13	8	9	7	0	6	11	-14	14	11
NW	11	19	38	-3	17	54	4	7	7	27	27	22
SD	11	24	61	-1	34	98	6	6	5	26	26	19
SW	11	15	20	0	8	10	4	4	4	26	27	23
UK	10	11	15	5	6	6	5	6	5	17	17	21

Table A.4: **Basis Return Predictability: OLS Results**

The table reports the results from a set of panel regressions of the form

$$r^{fut}_{i,t+1} = a_i + b_t + cBasis_{i,t} + \epsilon_{i,t+1}$$

$$r^{spot}_{i,t+1} = \alpha_i + b_t + \gamma Basis_{i,t} + \eta_{i,t+1}$$

where r^i_{t+1} is the return of asset i, a^i is the asset-specific intercept (or fixed effect), b_t are time-fixed effects, $Basis^i_t$ is the futures-spot basis in market i measured in the previous period, and c is the coefficient of interest that measures the return predictability coming from the basis. Panel A reports the results for regressions for a panel of global equities. Panel B reports the results for regressions for our panel of currencies. In each panel, the numbers in the first four columns correspond with regressions where the dependent variable is futures returns for a given market. The numbers in the second four columns correspond with regressions where the dependent variable is the spot return for a given market. The basis is scaled to be a weekly rate, so a coefficient of -1 indicates that subsequent returns in a market move one-for-one in the opposite direction of the basis. Each panel reports regression results for the full sample as well as for sub-samples of the data. Observations are sampled weekly. Standard errors are clustered by time and entity. t-statistics are reported in parentheses. The full-sample regressions are OLS regressions rather than WLS regressions, which is the case for the results of our main specifications reported in Table 2.

Panel A: Global Equities

	r_t = Futures Market Returns, c				r_t = Spot Market Returns, γ			
Jan. 2000-Dec. 2017	-5.03	-3.79	-5.00	-3.73	-3.51	-2.22	-3.42	-2.09
	(-3.40)	(-4.24)	(-3.15)	(-4.15)	(-2.48)	(-2.28)	(-2.25)	(-2.09)
Jan. 2000-Jun. 2007	-4.75	-3.08	-4.58	-2.89	-3.30	-1.64	-3.08	-1.39
	(-4.15)	(-3.33)	(-3.97)	(-3.07)	(-2.88)	(-1.78)	(-2.64)	(-1.47)
Jul. 2007-Dec. 2017	-5.52	-4.75	-5.58	-4.73	-3.93	-3.00	-3.90	-2.86
	(-1.70)	(-2.66)	(-1.59)	(-2.57)	(-1.25)	(-1.45)	(-1.14)	(-1.30)
Time FE	No	Yes	No	Yes	No	Yes	No	Yes
Entity FE	No	No	Yes	Yes	No	No	Yes	Yes

Panel B: Currencies

	r_t = Futures Market Returns, c				r_t = Spot Market Returns, γ			
Jan. 1989-Dec. 2017	-5.52	-5.80	-5.11	-5.11	-4.78	-4.99	-4.38	-4.33
	(-1.69)	(-2.05)	(-1.45)	(-2.00)	(-1.50)	(-1.82)	(-1.27)	(-1.75)
Jan. 1989-Dec. 1999	-1.00	-3.18	-0.97	-3.36	-0.45	-2.52	-0.43	-2.71
	(-0.59)	(-1.28)	(-0.57)	(-1.35)	(-0.28)	(-1.03)	(-0.27)	(-1.10)
Jan. 2000-Jun. 2007	-82.07	-46.48	-87.24	-35.64	-81.38	-45.67	-86.48	-34.64
	(-4.17)	(-3.89)	(-3.16)	(-1.41)	(-4.12)	(-3.80)	(-3.12)	(-1.35)
Jul. 2007-Dec. 2017	-13.81	-11.10	-17.57	-14.51	-12.65	-9.89	-16.31	-13.09
	(-1.91)	(-2.75)	(-1.37)	(-2.80)	(-1.75)	(-2.48)	(-1.26)	(-2.56)
Time FE	No	Yes	No	Yes	No	Yes	No	Yes
Entity FE	No	No	Yes	Yes	No	No	Yes	Yes

A.2 Expectations of Dividends Under the Physical Versus Risk-Neutral Measure

Throughout the paper, due to data availability, we use expectations of dividends under the physical measure to proxy for expectations of the dividends under the risk-neutral measure.[25] In this section, we provide back-of-the-envelope calculations to assess the impact of this choice.

Binsbergen and Koijen (2017) calculate that the monthly holding period returns of one-year maturity dividend strips range from 41 basis points (for the S&P 500) to 1.1 percent (for the Nikkei index), which are broadly in line with Binsbergen et al. (2012). These estimates present a conservative upper bound for the risk premium we expect to be embedded in the dividend expectations of the futures contracts used in our sample. The equity index futures contracts in our sample have maturities ranging from ten days to three months, and in all of the markets that we consider, dividends are announced one to three months prior to the dividend ex-date. Therefore, we expect the majority of dividends for an index to be known in our calculations of the basis (and thus have little risk premium associated with them). Put differently, we expect the majority of the risk premium earned in the one-year maturity dividend strips analyzed by Binsbergen and Koijen (2017) to be earned on ex-dividends beyond the maturity of the contracts that we use in the calculation of bases.

To analyze the impact that dividend risk premia have on our estimates of the basis, we calculate the basis under various assumptions for the dividend risk premium, which for simplicity we assume to be constant over time and across indices. For each day and each futures contract in our sample from 2007-2017, we calculate the annualized difference in the futures-spot basis that come from dividend risk premia by using the amount of ex-dividends expected until expiration and our assumed level of dividend risk premia. Subtracting these estimates from the futures-spot basis for each contract, we reconstruct the index level basis series for each equity index and rerun our tests.

For the global equities sample from June 2007 to December 2017, we rerun the return predictability regressions from Table 2 using our basis series constructed under various dividend risk premia estimates. We use monthly dividend risk premia estimates of 0 bps (the baseline estimates

[25]Traded dividend futures, which provide expectations of dividends under the risk-neutral measure rather than the physical measure, are only available for a subset of the indices in our sample. Additionally, with the exception of dividend futures traded on the S&P 500, the majority of dividend futures tend to trade at annual expirations, while the equity index futures in our sample generally trade at quarterly expirations. This mismatch prevents us from using data from dividend futures, even where such data is available, in our calculations of the basis.

reported in the main paper), 20 bps, 50 bps, 80 bps, 110 bps, and 140 bps. Table A.5 reports the results from these regressions. The regression coefficients are broadly similar under various dividend risk premia assumptions. Return predictability becomes slightly stronger as we increase the magnitude of the dividend risk premia. Increasing the dividend risk premia estimate for an equity index makes the basis we estimate more correlated with the index's "carry" (defined as the normalized difference between the futures and spot price of the index), from Koijen et al. (2018), which also has strong return predictability.

We also form cross-sectional global equity LMH Leverage Demand portfolios using the newly constructed futures-spot basis series. Table A.6 reports the annualized return statistics for these portfolios. Table A.7 reports the correlations of the portfolios with each other and with the global equity carry portfolio from Koijen et al. (2018). The returns of each of the series are highly correlated and realize a similar return over the sample. The correlations of each series decrease with our baseline results (and increase with the carry portfolio) as we increase the assumed level of dividend risk premia, although the performance results remain broadly similar. The analysis suggests that the cross-sectional return predictability of the futures-spot basis is not largely affected by dividend risk premia, and if anything, our assumption of no dividend risk premium understates our return predictability results.

Table A.5: **Global Equities Basis Return Predictability Under Dividend Risk Premia Assumptions**

	Global Equities, Jun. 2007-Dec.2017							
	r_t = Futures Market Returns, c				r_t = Spot Market Returns γ			
0 bps	-5.52	-4.75	-5.58	-4.73	-3.93	-3.00	-3.90	-2.86
	(-1.70)	(-2.66)	(-1.59)	(-2.57)	(-1.25)	(-1.45)	(-1.14)	(-1.30)
20 bps	-6.09	-5.02	-6.23	-5.09	-4.47	-3.23	-4.51	-3.16
	(-1.87)	(-2.79)	(-1.78)	(-2.75)	(-1.42)	(-1.52)	(-1.32)	(-1.41)
50 bps	-6.78	-5.35	-7.07	-5.56	-5.20	-3.56	-5.38	-3.63
	(-2.11)	(-2.98)	(-2.04)	(-3.00)	(-1.66)	(-1.66)	(-1.60)	(-1.61)
80 bps	-7.12	-5.38	-7.55	-5.75	-5.64	-3.70	-5.96	-3.91
	(-2.27)	(-3.12)	(-2.23)	(-3.18)	(-1.85)	(-1.78)	(-1.81)	(-1.78)
110 bps	-7.08	-5.15	-7.64	-5.66	-5.77	-3.64	-6.21	-3.98
	(-2.36)	(-3.17)	(-2.34)	(-3.28)	(-1.97)	(-1.86)	(-1.96)	(-1.91)
140 bps	-6.76	-4.75	-7.42	-5.36	-5.64	-3.44	-6.18	-3.88
	(-2.40)	(-3.12)	(-2.41)	(-3.30)	(-2.04)	(-1.91)	(-2.05)	(-2.01)
Time FE	No	Yes	No	Yes	No	Yes	No	Yes
Entity FE	No	No	Yes	Yes	No	No	Yes	Yes

Table A.6: **Global Equity LMH Leverage Demand Strategy Performance by Dividend Risk Premia Assumption**

Annualized Returns of Global Equity LMH Leverage Demand Strategy
Jun. 2007-Dec. 2017

Monthly Dividend Risk Premium (in Basis Points)	Average	Standard Deviation	Sharpe Ratio
0	7.89	6.96	1.13
20	8.14	6.76	1.20
50	7.59	6.61	1.15
80	7.11	6.53	1.09
110	7.10	6.59	1.08
140	7.09	6.67	1.06

Table A.7: **Global Equity LMH Leverage Demand Strategy Correlations by Dividend Risk Premia Estimate**

	0	20	50	80	110	140	Carry
0	1.00						
20	0.97	1.00					
50	0.89	0.95	1.00				
80	0.78	0.87	0.97	1.00			
110	0.67	0.77	0.91	0.97	1.00		
140	0.59	0.71	0.85	0.94	0.99	1.00	
Carry	-0.13	-0.02	0.14	0.27	0.39	0.45	1.00

A.3 Using Realized Dividends vs. Expected Dividends in Basis Construction

In the early part of our sample (from 2000 through the end of 2006), due to lack of data availability on dividend expectations, we proxy for the expectations of dividends on an index from time t until the expiration of a futures contracted traded on the index by using the realized ex-dividends on the index from time t until expiration. We argue and show that the use of realized dividends to proxy for expected dividends likely understates the relationship between the basis and expected returns in equity index futures. First, we argue that the use of realized dividends in the calculation of the basis is likely to have small impact. In all of the markets that we consider, dividends are announced one to three months prior to the ex-date, which is about the maturity of most of the contracts that we consider. We therefore expect the majority of dividends for an index to already be embedded in the expectations of the basis. Second, given the negative relationship we find between bases and subsequent market returns, the use of realized dividends to proxy for expected dividends in equity index futures in the early part of the sample, if anything, may present a conservative estimate of the relationship. Equity indices that realize negative dividend surprises (realized dividends less than expected) will have more negative bases when constructed using realized dividends, and vice-versa for equity indices that realize positive dividend surprises. We expected negative (positive) dividend surprises to be related to negative (positive) returns, so we expect the use of realized dividends may, if anything, understate the relationship between bases and subsequent returns.

For the 2007-2017 sample period, we re-run the basis return predictability regressions reported in Table 2, constructing the basis using realized dividends rather than expected dividends. Table A.8 displays the results from the regressions, in the row labeled *Realized Dividends*. The row labeled *Expected Dividends* in the table displays the corresponding regression results using expected dividends from Table 2. The results are very similar.

We also construct the LMH Leverage Demand strategy using realized dividends and compare it to the strategy using expected dividends. The two series are highly correlated (correlation of 0.89), but the strategy using realized dividends has slightly lower returns on average (Table **A.9**), consistent with a slight understatement of the strategy's profitability when using realized as opposed to expected dividends.

Table A.8: **Global Equities Basis Return Predictability**

Global Equities, Jun. 2007-Dec.2017								
	r_t = Futures Market Returns				r_t = Spot Market Returns			
Expected Dividends	-5.52	-4.75	-5.58	-4.73	-3.93	-3.00	-3.90	-2.86
	(-1.70)	(-2.66)	(-1.59)	(-2.57)	(-1.25)	(-1.45)	(-1.14)	(-1.30)
Realized Dividends	-5.00	-4.75	-5.09	-4.85	-3.51	-3.12	-3.54	-3.13
	(-1.42)	(-2.56)	(-1.36)	(-2.52)	(-1.02)	(-1.50)	(-0.97)	(-1.44)
Time FE	No	Yes	No	Yes	No	Yes	No	Yes
Entity FE	No	No	Yes	Yes	No	No	Yes	Yes

Table A.9: **LMH Leverage Demand Strategy Returns: Realized Dividends vs. Ex-ante Expected Dividends**

Annualized LMH Leverage Demand Strategy Returns *(2007-2017)*			
	Average	Std	Sharpe Ratio
Ex-Ante Dividend Expectations	7.62	6.87	1.11
Realized Dividends	6.52	6.99	0.93

Table A.10: **Markit Securities Finance Data Coverage Across Indices**

For each index, the table reports information on data coverage in the Markit Securities Finance (MSF) database. The "Average Index Weight" across time columns reports the time-series average of the percentage of an index for which we have securities lending data available. The "First Date with 80% coverage" reports the first date for which our data coverage in MSF exceeds 80% of the index weight of a given index. Lastly, number of observations is the number of valid, daily observations available in our dataset.

	Average Index Weight Coverage Across Time	**First Date with ¿ 80% Coverage**	**Number of Observations**
AU	99.9%	8/2/2004	3420
BD	99.4%	8/2/2004	3420
CN	98.5%	8/2/2004	3420
DJIA	100.0%	8/2/2004	3420
ES	94.6%	8/2/2004	3420
EUROSTOXX	97.0%	8/2/2004	3420
FR	98.6%	8/2/2004	3420
HK	79.6%	11/29/2007	3420
IT	92.0%	8/2/2004	3420
JP	85.3%	12/15/2005	3420
NASDAQ	99.8%	8/2/2004	3420
NL	81.8%	8/2/2004	3420
SD	99.3%	8/2/2004	3420
SW	99.4%	8/2/2004	3420
UK	97.5%	8/2/2004	3420
US	99.7%	8/2/2004	3420
USRU2K	99.9%	8/2/2004	3420
USSPMC	99.8%	8/2/2004	3420

A.4 Global Equities: Basis Return Predictability and US Indices

In our main results, our cross-section of eighteen equity indices includes five indices on US stocks: the DJIA, Nasdaq, the Russell 2000, the S&P500 and the S&P 400. Here, we analyze the robustness of our results to using alternative cross-sections that do not include as many American indices. We consider two cross-sections (in addition to the cross-section used in the main results). The first excludes all US indices except for the S&P500, and is labeled *SP500* in the results below. The second excludes all US indices, and is labeled *Ex US* in the results below.

We first repeat the full-sample regression for global equities from Table 2 for the two additional cross-sections. Table A.11 reports the results from the regressions alongside the regression results from the main table. The regression results are similar across the three cross-sections.

We next form two alternative global equity LMH Leverage Demand portfolios using the two alternative cross-sections, in addition to our baseline specification. Table A.12 displays the annualized mean, standard deviation, and Sharpe ratio of the global equity LMH Leverage Demand portfolio for our baseline specification, and the two alternative specifications. The returns of each of the specifications are similar. Table A.13 displays the correlations of the returns each of the alternative LMH strategies. The resulting portfolios are all highly correlated.

Table A.11: **Global Equities Basis Return Predictability**

	Global Equities, Jan. 2000-Dec. 2017							
	r_t = Futures Market Returns, c				r_t = Spot Market Returns, γ			
Main Results	-5.18	-4.08	-5.18	-4.05	-3.63	-2.46	-3.56	-2.33
	(-2.63)	(-3.73)	(-2.46)	(-3.67)	(-1.92)	(-1.97)	(-1.75)	(-1.81)
SP500	-5.77	-4.22	-5.84	-4.19	-4.06	-2.52	-4.09	-2.44
	(-3.34)	(-3.89)	(-3.29)	(-3.97)	(-2.38)	(-1.91)	(-2.34)	(-1.86)
Ex US	-5.59	-4.19	-5.64	-4.16	-3.88	-2.50	-3.90	-2.411
	(-3.28)	(-3.75)	(-3.24)	(-3.84)	(-2.31)	(-1.84)	(-2.27)	(-1.79)
Time FE	No	Yes	No	Yes	No	Yes	No	Yes
Entity FE	No	No	Yes	Yes	No	No	Yes	Yes

Table A.12: **Global Equities LMH Leverage Demand Strategy Performance**

	Mean	Stdev	Sharpe Ratio
LMH Leverage Demand	5.78	6.99	0.83
LMH Leverage Demand S&P500	6.59	7.75	0.85
LMH Leverage Demand ex US	7.08	8.27	0.85

Table A.13: **Global Equities LMH Leverage Demand Strategy Correlations**

	LMH	LMH S&P500	LMH ex US
LMH Leverage Demand	1.00		
LMH Leverage Demand S&P500	0.89	1.00	
LMH Leverage Demand ex US	0.87	0.98	1.00

A.5 Implied Interest Rates

We construct 3-month implied interest rates for S&P500 futures by linearly interpolating the interest rates embedded in the nearest and second-nearest to expiration futures contracts.[26] We construct the Treasury basis as the 3-month futures implied interest rate minus the 3-month US Treasury yield. We similarly construct the 3-month LIBOR basis as the 3-month futures implied interest rate minus 3-month LIBOR. The first column of Panel A Table A.14 reports the average values for the futures implied interest rates and bases that we construct, as well as the values for the corresponding 3-month benchmark interest rates.

Table A.15 reports the correlations between the LIBOR bases, Treasury bases, and the positions of dealers in S&P 500 futures contracts. Panel A reports correlations from June 2006 to December 2017 and Panel B reports correlations from January 2010 to December 2017. The 3-month LIBOR basis we estimate from futures contracts is 0.52 and 0.37 correlated with the 6- and 12-month LIBOR bases constructed using the vBDG box spreads in the longer sample (and 0.54 and 0.51 in the post-2010 sample). The 3-month Treasury basis we estimate from futures contracts is 0.81 and 0.80 correlated with the Treasury bases constructed using vBDG box spreads in the longer sample (and 0.44 and 0.41 correlated in the post-2010 sample). These numbers suggest commonality in the futures basis we estimate and the bases implied by the vBDG box spreads. The 3-month LIBOR and Treasury bases that we estimate are negatively correlated with dealers futures positions (correlations of -0.25 and -0.55 for the LIBOR basis in the two samples and -0.32 and -0.28 for the Treasury basis in the two samples), consistent with our story that the implied interest rates in futures contracts are related to the futures inventories of dealers. The correlations between dealer positions and the 6- and 12-month LIBOR and Treasury bases constructed using the vBDG box spreads are a bit more inconsistent. In the sample from 2006-2017, the correlations between the 6- and 12-month LIBOR bases and dealers' futures positions are 0.13 and -0.01. These correlations are -0.32 and -0.30 in the post-2010 sample. The correlations between the 6- and 12-month Treasury bases are -0.18 and -0.26 in the 2006-2017 sample, while they are 0.20 and 0.09 in the post-2010 sample. It is unclear whether the 6- and 12-month option-implied interest rates reflect the same types of leverage demand pressures that are present in the 3-month futures-implied interest rate we estimate.

[26] Because of poor behavior of scaling by maturity when maturity approaches zero, we only use the nearest expiration contract when it has more than ten days to maturity. This means that the maturity for the interest rate we extract is actually between three months and 3.5 months

Table A.14: **S&P 500 Derivatives Implied Interest Rates**

The table reports the average of S&P derivatives implied interest rates and benchmark interest rates. The first column corresponds with 3-month interest rates calculated from S&P 500 futures. The second and third columns correspond with 6- and 12-month interest rates calculated from S&P 500 "box spreads", in Binsbergen et al. (2019) (vBDG). The Treasury Basis is the difference between the implied interest rate and the same maturity US Treasury yield. The LIBOR Basis is the difference between the implied interest rate and the same maturity LIBOR rate. All values in the panel are in basis points.

S&P 500 Derivatives Implied Interest Rates Jan. 2004 - Dec. 2017			
	HMV	vBDG	vBDG
Avg. Implied Interest Rate	168.5	176.0	183.3
Avg. LIBOR	165.5	183.5	208.4
Avg. Treasury Yield	120.9	141.0	146.7
Avg. Treasury Basis	47.6	35.0	36.6
Avg. LIBOR Basis	3.0	-7.5	-25.1
Stdev. LIBOR Basis	22.7	20.4	25.0
Stdev. Treasury Basis	43.6	21.9	20.4
Maturity	3 months	6 months	12 months

Table A.15: **S&P 500 Interest Rate Spread Correlations**

The table reports correlations of the 3-, 6-, and 12-month LIBOR bases, the 3-, 6-, and 12-month Treasury bases, and dealer positions in S&P 500 index futures from the Traders in Financial Futures report. The LIBOR basis for a maturity is defined as the derivatives implied interest rate minus the LIBOR rate for the corresponding maturity. The Treasury basis for a maturity is defined as the derivatives implied interest rate minus the Treasury yield for the corresponding maturity. The 3-month implied interest rates are implied interest rates that we estimate from equity index futures contracts on the S&P 500. The 6- and 12-month implied interest rates are SPX option box spreads from Binsbergen et al. (2019). Panel A reports correlations estimated using data from June 2006 to December 2017. Panel B reports correlations estimated using data from January 2010 to December 2017.

Panel A: Correlations, Jun. 2006-Dec. 2017

	3m LIBOR Basis	6m LIBOR Basis	12m LIBOR Basis	3m Treas. Basis	6m Treas. Basis	12m Treas. Basis	Dealer Positions
3m LIBOR Basis	1.00						
6m LIBOR Basis	0.52	1.00					
12m LIBOR Basis	0.37	0.87	1.00				
3m Treasury Basis	0.18	-0.41	-0.17	1.00			
6m Treasury Basis	-0.21	-0.36	-0.08	0.81	1.00		
12m Treasury Basis	-0.22	-0.39	-0.04	0.80	0.94	1.00	
Dealer Positions	-0.25	0.13	-0.01	-0.32	-0.18	-0.26	1.00

Panel B: Correlations, Jan. 2010-Dec. 2017

	3m LIBOR Basis	6m LIBOR Basis	12m LIBOR Basis	3m Treas. Basis	6m Treas. Basis	12m Treas. Basis	Dealer Positions
3m LIBOR Basis	1.00						
6m LIBOR Basis	0.54	1.00					
12m LIBOR Basis	0.51	0.94	1.00				
3m Treasury Basis	0.87	0.30	0.28	1.00			
6m Treasury Basis	0.17	0.43	0.35	0.44	1.00		
12m Treasury Basis	0.16	0.36	0.38	0.41	0.87	1.00	
Dealer Positions	-0.55	-0.32	-0.30	-0.28	0.20	0.09	1.00

A.6 Currency LMH Leverage Demand Factor Spanning Tests with Alternate Factors

Table A.16: **Currency LMH Leverage Demand Factor Spanning Tests**

The table reports regression results for the cross-sectional currency LMH Leverage Demand portfolio and the currency LMH Leverage Demand timing portfolio's returns on a set of other portfolio returns of factors that have been shown to explain variation in currency returns: the value and momentum factors of Asness et al. (2013), the time-series momentum (TSMOM) factor of Moskowitz et al. (2012), and the Dollar (labeled as RX) and Carry Trade (labeled as HML_{FX}) risk factors from Lustig et al. (2011). Columns (1) and (2) report results where the Dollar and Carry Trade factors are formed using all currencies. Columns (3) and (4) report results where the Dollar and Carry trade factors are formed using only developed market currencies. The table reports intercepts or alphas (in percent) from these regressions, as well as the betas on the various factors. The last two rows report the R^2 from the regression and the information ratio, IR, which is the alpha divided by the residual volatility from the regression.

	(1) LMH XS	(2) LMH TS	(3) LMH XS	(4) LMH TS
Value	-0.02	0.09	0.01	0.13
	(-0.40)	(1.00)	(0.19)	(1.54)
Momentum	0.10*	0.09	0.07	0.07
	(1.74)	(0.92)	(1.43)	(0.69)
HML	0.26***	0.34***	0.33***	0.37***
	(6.52)	(4.76)	(10.71)	(6.51)
TSMOM	0.02	0.05	0.04*	0.07*
	(0.89)	(1.22)	(1.80)	(1.70)
RX	-0.26***	-1.04***	-0.21***	-0.80***
	(-4.73)	(-10.88)	(-5.65)	(-11.42)
α	0.16*	0.35**	0.15*	0.32**
	(1.69)	(2.02)	(1.73)	(1.97)
R^2	0.18	0.29	0.31	0.33
IR	0.33	0.40	0.34	0.38

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

A.7 Covered Interest Rate Parity Violations and Futures Positioning

In the main text of the paper, we provide evidence for the relationship between cross-currency bases and institutional investor positioning in currency futures traded on US exchanges. Here, we measure the relationship between the basis and the futures positions by investors classified as "Dealers / Intermediaries", "Hedge Funds" and the "Other Investor" category in the traders in financial futures report.

Table A.17 presents the results of regressing cross-currency bases on investor positioning in currency markets by Dealers, Institutional Investors, Hedge Funds, and Other category investors, as classified by the Traders in Financial Futures Report. Investor positioning is defined as in equation (8). The regression also includes controls for the local interbank offer rate ("Libor") and the Interbank Offer Rate minus the Overnight Indexed Swap Rate ("Libor_OIS"). Independent variables are standardized by subtracting the full sample mean and dividing by the full sample standard deviation of the variable. Standard errors are clustered by entity and time.

Cross-sectionally, hedge fund positioning is significantly negatively correlated with cross-currency bases; a one standard deviation change in leveraged investor positioning corresponds with a 7 to 9 basis point decrease in the basis. This is consistent with hedge funds taking the other side of hedging demand in futures markets, as suggested in other work (e.g. Moskowitz et al. (2012)), but is also consistent with hedge funds executing the carry trade (e.g. Brunnermeier et al. (2008)). Dealer positioning is significantly positively correlated with cross-currency bases; a one-standard deviation change in dealer positions corresponds with a 6-9 basis point increase in the basis. Dealer positions in futures markets largely appear to move in opposition to the position of Hedge Funds. The opposing signs on the Dealer and Hedge Fund positions are consistent with this fact. Other investor positioning tends to be positively related to the cross-currency basis, with coefficients ranging from 1.0 to 3.4. These coefficients become insignificant when controlling for entity fixed effects in the regression, suggesting limited ability to explain time-series variation in cross-currency bases.

Table A.17: **Cross-Currency Bases and Investor Positioning**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dealer	5.74**				8.73***		3.37*	0.02	
	(3.15)				(3.95)		(2.43)	(0.01)	
Institutional		5.95**			8.33**	5.22**	4.10**	2.02	2.03
		(2.79)			(3.55)	(2.97)	(2.61)	(1.03)	(1.22)
Hedge Funds			-9.26***			-7.90***			0.39
			(-4.14)			(-4.16)			(0.26)
Other				3.44**	3.42*	1.73	2.25	1.01	1.08
				(2.61)	(2.11)	(1.21)	(1.86)	(1.68)	(1.83)
Libor							-19.26***	6.33	6.33
							(-6.72)	(1.59)	(1.62)
Libor_OIS							11.99**	12.15**	12.17**
							(2.60)	(3.16)	(3.18)
R^2	0.24	0.26	0.31	0.23	0.35	0.35	0.60	0.74	0.74
Observations	3654	3654	3654	3654	3654	3654	3654	3654	3654
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Entity FE	No	No	No	No	No	No	No	Yes	Yes

t-statistics in parentheses.

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

A.8 Currency LMH Leverage Demand Strategy and the Carry Trade

Since the currency LMH Leverage Demand strategy is correlated to the currency carry trade, yet neither spans the other, we further explore the relationship between them to gain further insight into both strategies.

The previous literature (for example, Du et al. (2018)) highlight that "investment" currencies with high interest rates also tend to have more negative cross-currency bases, and "funding" currencies with lower interest rates have more positive cross-currency bases. Since the currency carry strategy sorts on local interest rates and the currency LMH Leverage Demand strategy sorts on bases, where interest rates and bases are correlated, the two strategies exhibit similar positions and returns.

We construct a carry portfolio for the currencies in our sample following equation (9), sorting currencies in our sample based on their one-month forward rates. Figure A.1 plots the average position of each currency in the carry and LMH portfolios. The positions in the two portfolios are correlated, although not perfectly so. Both the LMH portfolio and carry portfolio tend to hold long positions in the New Zealand and Australian dollars, and substantial short positions in the Japanese Yen. However, while the LMH portfolio is, on average, long the US dollar and short the British pound, the carry portfolio tends to be slightly short the US dollar and substantially long the British pound on average.

Next, we analyze the performance of the currency LMH strategy conditional on the performance of the currency carry strategy. We sort the returns of the currency carry portfolio into deciles based on the realized return of the carry portfolio. The first decile contains observations in the months with the bottom tenth percentile of currency carry returns, while the tenth decile contains observations in the months with the top tenth percentile of currency carry returns. In Figure A.2, we plot the returns of the LMH portfolio in each of these deciles, as well as the average value of the residuals plus the intercept from a regression of the currency LMH strategy returns on the returns of currency carry, value, momentum, time-series momentum, and a passive position in the currencies in our sample against the US dollar. The figure also plots the same quantities for a currency LMH strategy formed without taking positions in the U.S. dollar.

The plot suggests that the currency LMH Leverage Demand strategy returns are monotonically increasing by decile in the returns to the carry strategy. The currency LMH strategy earns an average negative 0.95 percent return during times when the carry strategy returns are in the bottom tenth percentile and earns an average 2.1 percent return when the carry strategy performance is in its top tenth percentile (these are in comparison to -4.0 percent and 3.8 percent in the same deciles for the carry strategy). Notably, the currency LMH strategy appears to earn a substantial portion of its alpha during the bottom tenth percentile of the currency carry returns. The strategy earns an average monthly alpha with respect to carry, value, momentum, time-series momentum, and the dollar factor of 59 bps during the bottom tenth percentile of currency carry returns.

One potential explanation for why the currency LMH strategy earns higher alpha when the carry portfolio crashes may be related to the safe haven status of the US dollar. Since the LMH portfolio holds a long position in the US dollar on average, the strategy may outperform simply due to dollar appreciation during carry downturns when investors flock to the dollar. However, we also show that a currency LMH strategy formed without taking positions in the US dollar earns similar returns across the carry strategy performance deciles, indicating that positioning in the USD cannot explain the conditional alpha of the currency LMH strategy during carry downturns.[27]

Although both exhibit independent variation, the currency LMH Leverage Demand portfolio and currency carry portfolio are highly correlated, suggesting they load on a common factor.[28] However, the currency LMH portfolio does not have the same negative skewness that the currency carry portfolio famously demonstrates, and tends to earn alpha during the worst performance periods of the currency carry factor. These results suggest perhaps that while a portion of the returns of the carry trade may be compensation for crash risk, as suggested by Brunnermeier et al. (2008), a more substantial portion may be compensation for loading on a common risk factor (e.g., Lustig and Verdelhan (2007, 2009); Jurek (2014) and Bekaert and Panayotov (2019)). Our results highlight that the currency LMH Leverage Demand and currency carry factors are related, but that each contains unique information for exchange rates not spanned by the other.

[27]The outperformance of the currency LMH Leverage Demand strategy during downturns of the carry portfolio appears to come mostly from the short side of the currency LMH portfolio. See Figure A.3.

[28]In Table A.18, we regress the returns of the currency currency carry factor on the currency LMH Leverage, value, momentum, time-series momentum factors and on the returns of holding an equal-weighted basket of developed market currencies against the USD. The portfolio earns an alpha of 11 basis points per month, with an information ratio of 0.34. The multivariate beta of the currency carry portfolio to the currency LMH Leverage Demand portfolio is 0.61 in the sample.

Figure A.1: **Currency Carry Portfolio and LMH Leverage Demand Portfolio Positions**

The figure plots the average position of each currency in our sample in the currency LMH Leverage Demand portfolio and in a currency carry portfolio formed following equation (9) by sorting assets based on their one-month forward rates.

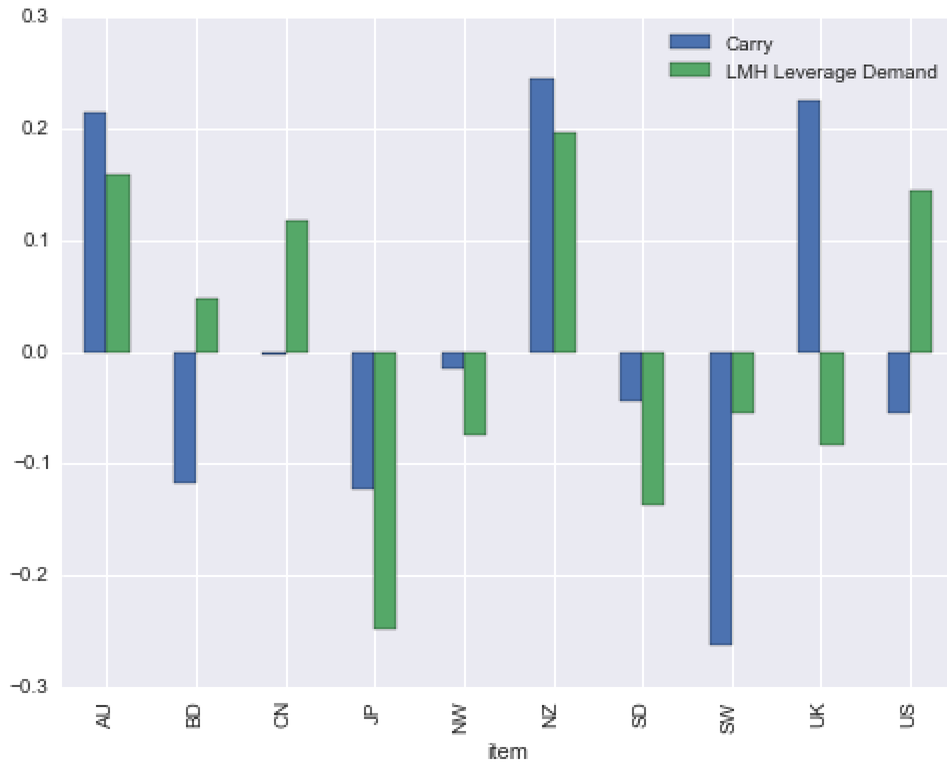

Figure A.2: **Currency LMH Leverage Demand Portfolio Returns by Carry Decile**

The figure sorts the currency carry returns from Koijen et al. (2018) into deciles based on the realized performance of the currency carry strategy. The first decile corresponds with the bottom tenth percentile of carry portfolio returns and the tenth decile corresponds with the top tenth percentile of currency carry returns. The figure plots the average return of the currency LMH Leverage Demand strategy, "LMH Leverage Demand," the average value of the residuals plus the intercept ("Residual") from a regression of the currency LMH Leverage Demand strategy returns on the returns of currency carry, value, momentum, time-series momentum, and a passive position in the currencies in our sample against the USD. The figure also plots the same quantities for a currency LMH Leverage Demand strategy formed without taking positions in the USD (labeled with the suffix "ex US").

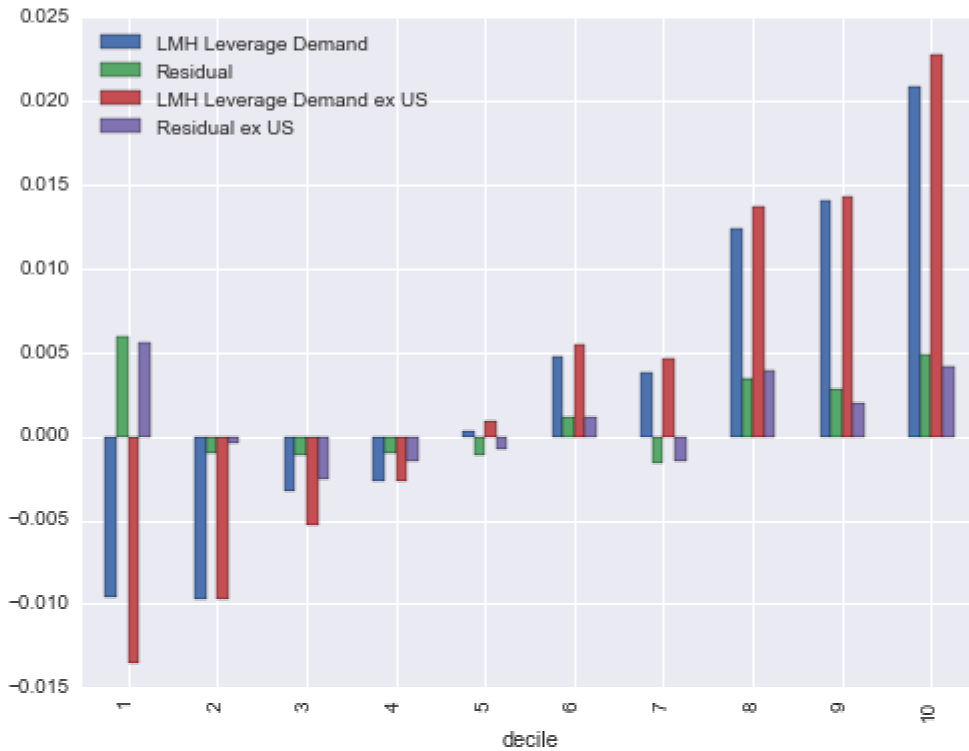

Figure A.3: **Currency LMH Leverage Demand Portfolio Returns by Carry Decile**

The figure plots the average return of the long and short positions of the currency LMH Leverage Demand strategy and the currency carry strategy across currency carry decile performance. Specifically, we first sort the currency carry returns from Koijen et al. (2018) into deciles based on the realized performance of the currency carry strategy. The first decile corresponds to the bottom tenth percentile of carry portfolio returns and the tenth decile corresponds to the top tenth percentile of currency carry returns.

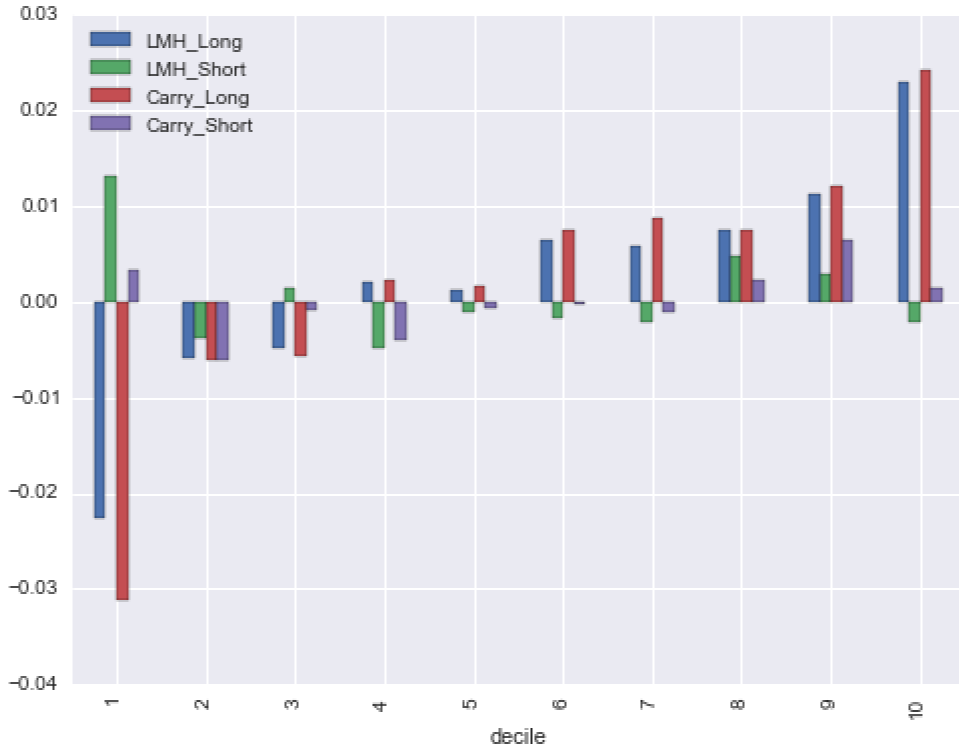

Table A.18: **Currency Carry Spanning Test**

The table reports regression results for the currency carry factor (from Koijen et al. (2018)) on the cross-sectional currency LMH Leverage Demand portfolio's returns, the returns to a passive long position in developed market currencies against the US dollar, the currency value and momentum factors of Asness et al. (2013), and the currency time-series momentum (TSMOM) factor of Moskowitz et al. (2012). The table reports the intercept or alpha (in percent) from the regression, as well as the betas on the various factors for the LMH Leverage Demand strategies. The last two rows report the R^2 from the regression and the information ratio, IR, which is the alpha divided by the residual volatility from the regression.

	Carry
Value	-0.0764
	(-1.59)
Momentum	0.0566
	(0.99)
LMH Leverage Demand	0.617***
	(12.07)
TSMOM	-0.0444*
	(-1.79)
PassiveLong	0.361***
	(8.77)
α	0.168*
	(1.76)
R^2	0.394
IR	0.342

t-statistics in parentheses.

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