Beyond Basis Basics: Liquidity 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 – the futures-cash basis – capture information about liquidity demand for equity market exposure in global markets. We show that the basis co-moves with dealer and investor futures positions, is contemporaneously positively correlated with futures and spot market returns, and negatively predicts futures and spot returns. These findings are consistent with the futures-cash basis reflecting liquidity demand that is common to futures and cash equity markets. We find persistent supply-demand imbalances for equity index exposure reflected in the basis, giving rise to an annual premium of 5% to 6%.

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We study deviations from the textbook law of one price in equity index futures. In particular, we consider the difference between the futures price and the hypothetical price of replicating the futures contract by borrowing cash at the benchmark rate and purchasing shares in the underlying. We refer to this pricing gap as the *futures-cash basis*, or simply, the *basis*.[1] The futures-cash basis reflects a wedge between benchmark borrowing rates and the true borrowing rates that arbitrageurs face to finance their spot market positions. In equilibrium, the basis emerges from a combination of supply-side frictions that intermediaries face, such as balance sheet costs, and the amount of futures demand to be intermediated.[2] While recent work focuses primarily on the futures supply-side frictions that give rise to the basis, we focus on the demand side, identifying several new implications that find support in the data. Focusing on the demand side also allows us to explain *cross-sectional* variation in the sign and magnitude of the basis across equity indices. Such heterogeneity is substantial in the data and has not been extensively explored in previous work.

In addition to reflecting dealer financing costs, we argue that the futures-cash basis in global equity markets reflects liquidity demand that is common to both futures markets and spot mar-

[1]The quantity we study is distinct from the difference between futures prices and spot prices, which is sometimes referred to as the *futures-spot basis*. The futures-cash basis that we study is also sometimes referred to by practitioners as the *implied repo rate*, as we discuss in Section V.B. The existence of the futures-cash basis in equity index markets is documented by Cornell and French (1983), Figlewski (1984), MacKinlay and Ramaswamy (1988), Harris (1989), Miller, Muthuswamy, and Whaley (1994), Yadav and Pope (1994), and Chen, Cuny, and Haugen (1995), who present mixed evidence regarding whether the basis represents an arbitrage. Roll, Schwartz, and Subrahmanyam (2007) link the futures-cash basis in NYSE composite futures with market liquidity.

[2]Other settings in which financing frictions lead to deviations from the law of one price include equity carve outs (Lamont and Thaler (2003)), equity index options (Constantinides and Lian (2021), Chen, Joslin, and Ni (2018), Golez, Jackwerth, and Slavutskaya (2018)), currencies (Garleanu and Pedersen (2011), Borio, McCauley, McGuire, and Sushko (2016), Du, Tepper, and Verdelhan (2018)), TIPS/Treasuries (Fleckenstein, Longstaff, and Lustig (2014)), CDS/bonds (Duffie (2010), Garleanu and Pedersen (2011)), and corporate bonds (Lewis, Longstaff, and Petrasek (2021)).

kets. To illustrate our argument, we present a model of liquidity demand, in which liquidity traders and informed traders (who we refer to jointly as “end users” or “customers”) submit market orders for equity index exposure to futures and spot markets, and orders are correlated across the two markets. Dealers in futures markets meet futures demand and hedge their risk exposure by trading in the spot market with risk-averse liquidity providers. Futures dealers face marginal holding costs that increase with the amount of demand they intermediate, which are reflected as the basis between futures prices and spot prices, with a more positive (negative) basis corresponding to longer (shorter) futures demand. Liquidity providers in the spot market meet both direct demand from customers and hedging demand from futures dealers, and they require compensation for holding inventory opposite informed demand. Liquidity provider compensation is reflected by an increase in prices contemporaneous with demand that reverts after demand abates. Futures prices rise and fall by more than spot prices, corresponding to the impact of futures dealer balance sheet costs. The trading behavior of market participants is illustrated in Figure 1.

–Figure 1 here–

The model generates three novel predictions. The first is that the futures-cash basis is negatively correlated with dealers’ futures positions and positively correlated with customers’ futures positions, stemming from the increasing marginal costs that futures dealers face in meeting demand. The second prediction is that futures *and* spot returns are contemporaneously positively correlated with changes in the basis (with the same sign). Changes in the basis reflect order flow for an index, which is reflected in increasing futures and spot prices. This mechanism also predicts that changes in dealers’ futures positions are contemporaneously negatively correlated with futures and spot returns, while changes in customers’ positions are contemporaneously positively correlated with futures and spot returns. The third prediction is that the basis negatively predicts futures returns and spot returns, and with the same sign. The basis captures the inventory of spot market liquidity providers, with more positive inventory corresponding to positive futures and spot returns. A corollary is that dealers' futures positions positively predict subsequent futures and spot returns, and customers' futures positions negatively predict futures and spot returns.

We test the first prediction by examining weekly data on investor futures positions from the U.S. Commodity Futures Trading Commission (CFTC). Dealer net positions are strongly negatively related to the basis, while the net positions of hedge funds and institutions are positively related to the basis. Across equity indices, at a given point in time, the basis varies positively with the strength of opposing positions between dealers and end users in the cross section. In addition, for a given futures contract, the basis varies over time with the size of the opposing positions of dealers and end users. These results are consistent with dealers taking the other side of customer demand for futures, with dealers' marginal costs (and the size of the basis) increasing with end-user demand.

To test the second and third predictions of the model, we examine the relationship of the basis to equity index futures and spot market returns. Consistent with the second prediction of the model, a one-standard-deviation increase in the basis corresponds to contemporaneous positive weekly returns in futures and spot markets of 14 to 47 basis points (bps), depending upon the specification. We also find that the futures-cash basis negatively predicts subsequent weekly futures returns and spot market returns that are two to five times larger than the magnitude of the basis. Notably, the contemporaneous and predictive relationships between the basis and returns are in the same direction for spot and futures returns, as uniquely predicted by the model. For both predictions, we find evidence that the relationships hold in both time-series comparisons for each index and cross-sectional comparisons across indices. Using CFTC futures position data, we test the corollaries to the second and third predictions relating investor positions to futures and spot market returns. We find evidence consistent with the model's predictions.

Delving deeper into the third prediction, we quantify the return predictability associated with the basis by constructing two weekly rebalanced trading strategies. The first is a cross-sectional trading strategy that goes long equity indices with a more negative basis and short indices with a more positive basis. The second strategy is an index timing strategy that takes long positions in equity indices with a positive basis relative to their histories, and short positions in indices with a negative basis relative to their histories. The trading strategies earn substantial profits: the annualized Sharpe ratio of the cross-sectional strategy is 0.86 (0.62) when implemented in futures contracts (spot markets), and that of the timing strategy is 0.69 (0.54) when implemented in futures contracts (spot markets).

The second and third predictions are unique to our explanation that the futures-cash basis captures liquidity demand reflected in both futures and spot markets. Supply-side frictions, such as balance sheet costs, are important for delivering the predictions that relate futures demand with the basis and for allowing us to empirically detect futures demand in the data. However, futures prices move substantially more than implied by the basis, and futures supply-side frictions alone carry no predictions for the relationship between the basis and spot market prices. These facts require a demand-based explanation, which we provide. Moreover, the empirical results allow us to distinguish theories of futures demand. One alternative theory is that because of their low transaction costs, high liquidity, and embedded leverage, futures contracts are the preferred instrument for sophisticated traders to trade on their information. However, if futures demand were primarily informed, we would not expect to observe that the basis (and futures positions) negatively predict spot market returns. While some futures demand may be informed, our results are consistent with customers using futures contracts as instruments to demand equity market liquidity.

A key assumption for our story is that liquidity demand is highly correlated across futures and spot markets. We provide evidence to support this assumption by using data on flows into exchange-traded funds (ETFs) and open-end funds that are benchmarked to the U.S. indices underlying the futures contracts in our sample. These funds primarily purchase shares in the spot market when faced with inflows, corresponding to spot market liquidity demand. We find that flows into ETFs and open-end funds are strongly related to changes in the futures-cash basis and to changes in the futures positions of dealers and hedge funds. The evidence is consistent with hedge funds using both futures and ETFs to rebalance their equity exposure and underscores that the basis captures demand for equity index exposure reflected in both futures and spot markets.

Next, we more closely study the role that intermediary costs play in the basis, following three different approaches. First, for a subset of our sample, we obtain pricing quotes on total return swaps. These quotes are reported as spreads relative to benchmark interest rates, and provide a direct measure of the all-in costs that dealers may face to provide leveraged exposure to an equity index. We find that these quotes are highly correlated with the futures-cash basis and have strong return predictability in futures and spot markets. The results using total return swap pricing thus provide additional evidence on the role of the financing frictions that dealers face.

Second, we study a mechanism through which dealers' marginal financing costs are increasing in the futures demand they intermediate. Equity repo (or related, securities lending) is the preferred financing strategy for equity index futures dealers, in which they borrow cash using their hedge positions as collateral. The benefit to dealers for using index shares as collateral increases with the demand to borrow (and short) shares of the index, and decreases with the corresponding supply.[3] Ceteris paribus, an increase in long futures demand for an index, and dealers' subsequent use of the index's shares as collateral, corresponds to an increase in the supply of shares available to borrow. Accordingly, the marginal financing cost for that index, and the futures-cash basis, increase. We test this mechanism using data on security lending fees. We find evidence consistent with the mechanism.

[3]For our treatment, equity repo is largely interchangeable with securities lending, whereby shareholders lend the securities out in exchange for cash. Song (2016) presents a model in which equity repo financing is the preferred financing strategy for intermediaries in equity derivatives markets.

Third, we study the role of balance sheet costs in the futures-cash basis. In our model, the basis is a function of the amount of demand for that asset and the cost of balance sheet space. We use the magnitude of pricing deviations in international markets and other asset classes to proxy for variation in the cost of balance sheet space, and show that it explains variation in the signed basis for U.S. equity indices when interacted with the signed positions of futures dealers.

Our results connect the literature on intermediation costs to the literature on end-user demand, dealer inventories, and asset prices (De Roon, Nijman, and Veld (2000), Chordia, Roll, and Subrahmanyam (2002), Bollen and Whaley (2004), Garleanu, Pedersen, and Poteshman (2009), Hendershott and Menkveld (2014), Greenwood and Vayanos (2014), Boons and Prado (2019), and He, Khorrami, and Song (2022)), making clear that financing rates and asset demand are interrelated. Our paper is particularly related to a growing body of work that emphasizes the role that institutional demand plays in prices across a variety of asset classes (Klingler and Sundaresan (2019), Koijen and Yogo (2019), Greenwood and Vissing-Jorgensen (2019), Koijen, Richmond, and Yogo (2020)).[4] While other studies focus primarily on the effects of institutional demand in individual stocks or specialized assets, we show that institutional demand forces can drive variation in the prices of entire equity markets, in line with recent evidence presented by Koijen and Gabaix (2020).

The rest of the paper is organized as follows. Section I presents a model of liquidity demand and outlines testable predictions. Section II presents the data and methodology for calculating the futures-cash basis in equity index markets. Section III tests predictions from the model relating the basis, dealer inventory positions, and returns. Section IV presents evidence on the relationship between liquidity demand in futures and spot markets. Section V more closely studies the role of dealer costs and financing frictions. Section VI concludes.

[4]In a similar spirit, 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.

I. Model of Liquidity Demand for Futures

We present a stylized model of liquidity demand to guide our empirical investigation.[5] In the model, futures dealers meet customer demand for futures and hedge their risk by trading in the spot market, paying a balance sheet cost that is reflected in the basis. Risk-averse spot-market liquidity providers meet direct demand from customers and dealer hedging demand, requiring compensation for holding inventory. The mechanics of this trading are depicted in Figure 1. The model motivates a set of predictions that relate investor positions, the basis, and futures and spot market returns.

A. *Model Setup*

There are N assets, $i = 1, \ldots, N$, in zero net supply, a futures contract traded on each risky asset in each period in zero net supply, and a riskless asset in perfectly elastic supply with a zero interest rate. Time is discrete, $t = 0, 1, \ldots, T$. There are four groups of market participants: informed traders, liquidity traders, futures dealers, and spot-market liquidity providers. We refer to the first two groups jointly as end users or customers.

The value of asset i in the final period T is

$$v_T = v_{i,0} + \sum_{t=1}^{T} \delta_{i,t} + \sum_{t=1}^{T} \epsilon_{i,t} + \sum_{t=1}^{T} e_t, \tag{1}$$

which is paid as a terminal dividend. The innovations $\delta_{i,t}$, $\epsilon_{i,t}$ and e_t are jointly normal, uncorrelated across time, and have variances σ_δ^2, σ_ϵ^2, and σ_e^2, respectively. The innovations $\delta_{i,t}$ and $\epsilon_{i,t}$ are uncorrelated across assets, while e_t is common to all assets.

A futures contract traded in period t is a promise to deliver one unit of asset i at the be-

[5]The model here is a simple extension of the model in Nagel (2012), which itself draws heavily from prior models of liquidity provision, such as Kyle (1985), Grossman and Miller (1988), and Admati and Pfleiderer (1988).

ginning of period $t+1$. The prices of asset i and the futures contract on i are denoted by $P^s_{i,t}$ and $P^f_{i,t}$, respectively. The basis at time t is defined as the difference between the futures price and the hypothetical price of replicating the futures contract in the spot market. As there are no intermediate dividends and the interest rate is zero, this replicating price is simply the spot price. Hence, the basis is $B_{i,t} \equiv P^f_{i,t} - P^s_{i,t}$.

Informed traders and liquidity traders trade by submitting a constant fraction θ of their demand for exposure to the risky asset as market orders for the futures contract and $(1-\theta)$ of their demand as market orders for the spot asset. Liquidity traders demand a random, exogenous amount $z_{i,t}$ of asset i in period t, where $z_{i,t}$ is normal, independent and identically distributed over time and across assets, uncorrelated with $\delta_{i,t}$ and $\xi_{i,t}$, and has variance σ^2_z.

The signals $\epsilon_{i,t}$ and e_t are public and observed at time t by all market participants. The innovation $\delta_{i,t}$ becomes public information at time t, but informed traders receive a private signal in the previous period, $s_{i,t-1} = \delta_{i,t}$, that provides them a short-lived informational advantage. The representative informed trader is myopic with exponential utility. As in Nagel (2012), her asset demand is linear in her signal,

$$y_{i,t} = \beta s_{i,t}, \tag{2}$$

where β captures the aggressiveness with which informed traders trade on their private signals.[6] The total customer demand for asset i via the spot and futures markets is $x_{i,t} = y_{i,t} + z_{i,t}$.

Futures dealers engage in riskless futures-cash basis arbitrage. For each index i, the representative dealer takes a position $d_{i,t}$ in the spot market and a position of $-d_{i,t}$ in the futures market such that the positions solve the objective function

$$\max_{d_{i,t}} B_{i,t} d_{i,t} - \frac{C_t}{2} d^2_{i,t}. \tag{3}$$

[6] The expression for β is nearly identical to the one derived in Nagel (2012).

Dealers trade off profits from the basis trade against $\frac{C_t}{2}d_{i,t}^2$, which can be considered a holding cost that dealers face to meet demand, where $C_t > 0$ is a constant. The quadratic total cost means that dealers face marginal costs for each asset that increase in the demand for that asset.[7] One interpretation is that C_t captures the cost of expanding dealer balance sheets that is common across all assets (e.g., from leverage constraints). In reduced form, the increasing marginal costs may reflect increasing costs to finance positions in asset i, and may also reflect dealers' risk-management against holding large positions in any given basis trade.[8]

Futures market clearing ($d_{i,t} = \theta x_{i,t}$) yields an expression for the basis:

$$B_{i,t} = C_t \theta x_{i,t}.$$

Spot market liquidity providers satisfy the demand for $\theta x_{i,t}$ units of asset i from futures dealers and $(1-\theta)x_{i,t}$ units of asset i coming directly from end users. The representative competitive liquidity provider is myopic with CARA utility. Her asset demand is given by

$$m_{i,t} = \gamma \left(E[\delta_{i,t+1}|\mathcal{M}_t] + v_{i,t} - P_{i,t}^s \right), \tag{4}$$

where $\mathcal{M}_t$ is her information set at time t. The aggressiveness with which liquidity providers supply liquidity is represented by γ and is decreasing in the amount of risk and increasing in the risk-bearing capacity of the market-makers.[9] Because $z_{i,t}$ and $\delta_{i,t+1}$ are independently normal,

[7]We assume a quadratic form simply to provide an expression for prices that is linear in demand. Our results depend only on the convexity of the holding cost, which we discuss in more detail after presenting the model.

[8]One reason that marginal financing costs for asset i may be increasing in demand is that equity repurchase and securities lending markets, where dealers prefer to obtain financing for equity market positions, are highly segmented (Hu, Pan, and Wang (2021)). There are likely a limited number of other market participants willing to accept the asset as collateral, or that want to borrow the asset against cash and sell it short.

[9]For example, γ can vary because of actual risk-aversion (e.g., as assumed in Grossman and Miller (1988)) or because constraints induce liquidity providers to behave as if they are risk-averse (e.g., Value-at-Risk constraints,

liquidity providers' expectation of $\delta_{i,t+1}$ is given by

$$E\left[\delta_{i,t+1}\middle|\,\mathcal{M}_t\right] = \frac{\beta\sigma_\delta^2}{\beta^2\sigma_\delta^2+\sigma_z^2}x_{i,t} \equiv \phi x_{i,t}, \tag{5}$$

where ϕ is defined to solve the equation and captures the informativeness of demand, $x_{i,t}$, about the forecastable component of period $t+1$, $\delta_{i,t+1}$. Spot market clearing ($x_{i,t}+m_{i,t}=0$) provides expressions for the equilibrium prices of asset i and the futures contract written on asset i:

$$P_{i,t}^s = \left(\frac{1}{\gamma}+\phi\right)x_{i,t}+v_{i,t}, \tag{Spot Price}$$

$$P_{i,t}^f = P_{i,t}^s + C_t\theta x_{i,t}. \tag{Futures Price}$$

The equilibrium dollar return for asset i and the period t futures contract on i are defined as

$$R_{i,t+1}^s \equiv P_{i,t+1}^s - P_{i,t}^s = e_{t+1}+\epsilon_{i,t+1}+\eta_{i,t+1}+\left(\frac{1}{\gamma}+\phi\right)x_{i,t+1}-\frac{1}{\gamma}x_{i,t}, \tag{Spot Returns}$$

$$R_{t+1}^f \equiv P_{i,t+1}^s - P_{i,t}^f = R_{i,t+1}^s - C_t\theta x_{i,t}, \tag{Futures Contract Returns}$$

where $\eta_{i,t+1} \equiv \delta_{i,t+1}-\phi x_{i,t}$ is the component of $\delta_{i,t+1}$ that is unpredictable for liquidity providers using period t information.

The basis for asset i scales linearly with the number of futures contracts demanded, reflecting dealer holdings costs to meet futures demand. Both futures returns and spot returns have an unpredictable component at time $t+1$, which comes from unexpected order flow, and a predictable component, which is the compensation earned by liquidity providers. Because $s_{i,t+1}$ and $z_{i,t+1}$ are independent across time, $x_{i,t+1}$ is not predictable at time t. For the spot returns, $-x_{i,t}$ represents the expected component of period $t+1$ order flow, and $-\frac{1}{\gamma}x_{i,t}$ is the

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as in Adrian and Shin (2010), or funding constraints, as in Brunnermeier and Pedersen (2008)).

predictable component of returns that compensates the liquidity provider for bearing inventory risk. Futures returns are equal to spot returns plus an additional predictable component, $-C_t\theta x_{i,t}$, which comes from dealers' holding costs and represents futures converging to the spot price at delivery.

B. *Model Predictions*

PREDICTION 1: *The (signed) futures-cash basis is positively related to long futures demand from customers and negatively related to dealers' futures positions.*

This prediction follows from the definition of the basis from the model ($B_{i,t} = C_t\theta x_{i,t}$, where $\theta x_{i,t}$ is customer demand for futures on asset i). The basis has the same sign as customer demand and scales proportionally with the amount of customer demand.

This prediction shows how the *signed* basis behaves, in contrast with recent work that highlights the *magnitude* of the basis (for example, Du, Tepper, and Verdelhan (2018) and Andersen, Duffie, and Song (2019)). However, it is not unique to our story and also holds under alternative explanations, for example, if the basis represents an arbitrage opportunity.

PREDICTION 2: *Changes in the basis are contemporaneously positively correlated with futures returns and spot returns (with the same sign).*

COROLLARY: *Changes in dealers' futures positions are contemporaneously negatively correlated with futures returns and spot returns. Changes in customers' futures positions are contemporaneously positively correlated with futures returns and spot returns.*

This prediction stems from each variable's relationship with total order flow, $\Delta x_{i,t+1} \equiv x_{i,t+1} - x_{i,t}$. Changes in the basis, futures market returns, and spot market returns, are all increasing in order flow. The contemporaneous correlations should be stronger in futures, as dealer balance sheet costs are reflected only in futures prices, not in spot prices. The corollary follows because order flow is directly captured by changes in dealers' and customers' futures positions.

This prediction is unique to our model. Other explanations that do not focus on the common spot and futures market demand captured by the basis might predict that the basis is contemporaneously increasing with futures contract returns, but they would predict that the basis should be either contemporaneously negatively related to spot market prices or unrelated.

PREDICTION 3: *The basis negatively predicts subsequent futures returns and spot returns (with the same sign*

COROLLARY: *Dealers' futures positions positively predict subsequent futures returns and spot returns, and customers' futures positions negatively predict subsequent futures returns and spot returns.*

This prediction directly follows from the fact that period $t+1$ returns are negatively related to the total demand in period t, $x_{i,t}$, reflecting compensation to spot market liquidity providers. The predictive relationship should be stronger for futures returns, which include an additional basis term. The corollary follows because dealers' and customers' positions capture $x_{i,t}$.

This prediction is also unique to our story. Alternative explanations may suggest that the basis negatively predicts futures returns, but they would predict either no relationship between the basis and subsequent spot returns or a positive relationship.

B.1. Cross-Sectional Predictions

Each of the predictions holds as a cross-sectional prediction as well as an asset-level prediction. For example, Prediction 2 states that we expect an increase in the basis to correspond to positive spot and futures market returns for a given index. The model also predicts that in cross-sectional comparisons, indices with larger increases should have larger futures and spot market returns.

C. *Discussion of the Model*

An important ingredient for the model's main insights is that dealers face holding costs that increase in demand. One of these costs is C_t, which is common to all assets and may capture the cost of expanding dealer balance sheets, including regulatory capital requirements and shareholder costs from debt overhang (as discussed in Andersen, Duffie, and Song (2019) and Fleckenstein and Longstaff (2020)).[10] Another of these costs is asset-specific, with higher marginal holding costs for assets that are more heavily demanded by customers.[11] Dealers may employ position limits, which may partially explain the higher marginal costs for assets in greater demand. Additionally, futures dealers prefer to borrow cash using their hedge positions as collateral. Holding fixed the demand for borrowing shares, additional futures demand pushes dealers to increase the supply of shares available to borrow, which all else equal decreases the marginal benefit they receive from using the shares as collateral. In turn, futures demand is reflected as higher marginal funding costs for dealers. We discuss this channel in more detail in Section V.

Another important ingredient for the model is that informed traders and liquidity traders submit trades in both the futures market and the spot market. Liquidity providers in the spot market meet that demand either directly or intermediated via dealers, and require compensation for doing so. Two natural questions arise: why do investors trade in futures markets at all, if there is an additional associated cost (the basis), and, how realistic is the model's asumption that informed and liquidity demand are perfectly correlated across futures and spot markets?

With respect to the first question, futures allow investors to gain substantial equity exposure in a cash-efficient way by posting a small amount of margin relative to the notional exposure

[10] In addition to balance sheet costs, the basis may also partially reflect imperfect competition. See Wallen (2022).

[11] This assumption is also made in other recent works studying deviations from the law of one price, for example, Liao and Zhang (2020), who study deviations from covered interest rate parity.

they gain. Margin trading in cash equities is more expensive. Additionally, to replicate an index, an investor has to purchase each stock in the index, whereas they only execute one transaction to buy index futures. Investors that are not informed about cross-sectional differences in single stock returns may prefer trading in a single "basket" security to avoid trading costs from adverse selection (Subrahmanyam (1991) and Gorton and Pennacchi (1993)).

With respect to the second question, the model delivers the same predictions so long as futures demand is strongly related (but does not have to be perfectly related) to the demand that spot market liquidity providers face. This assumption is plausible as some classes of investors, for example, hedge funds and institutional investors, trade in both futures and spot markets. We also provide empirical support for this assumption in Section IV, where we find a strong relationship between hedge fund demand for futures on an index and flows into ETFs and mutual funds benchmarked to that index. Finally, since dealers hedge their futures positions in the spot market, there should be some connection between demand in both markets, though this channel likely explains only a small component of that demand.

Importantly for our story, liquidity demand is commonly reflected in both the futures market and the spot market. The predictions of our model stand in contrast with another plausible story that futures contracts, given their low transaction costs and high liquidity, are the preferred instrument for sophisticated traders to trade on their information. Under this alternative story, the futures demand captured by the basis should not negatively predict returns in the spot market. We test this alternative story and conclude that while some traders may trade futures for information-based reasons, equity index futures markets are an important venue for market participants to demand liquidity for equity exposure.

II. Data and Methodology

In this section we describe the data and methodology for computing the basis and we present summary statistics.

A. Data

We study listed futures on 18 developed equity market indices: S&P 500 (U.S.), NASDAQ (NASDAQ), Russell 2000 (U.S.RU2K), S&P 400 MidCap (U.S.SPMC), 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). All futures are cash settled. The sample period is the period over which we have intraday pricing data used to compute the basis, namely January 2000 to December 2017.

We compute futures returns using daily settlement prices for the nearest-to-expiration futures contract for each index, excluding returns on collateral from transacting. These are essentially excess returns. We calculate excess spot market returns for each index using the daily gross total return of the index, assuming all dividends are not taxed and are fully reinvested, less the local interbank rate. Data used to compute returns come from Bloomberg.

B. Computing the Basis

The price of a futures contract can be expressed as

$$F_t = S_t \left(1 + r_t^f\right) - \mathbb{E}_t^Q(D_{t+1}), \tag{6}$$

where F_t is the futures price, S_t is the spot price, r_t^f is the embedded financing rate, and $\mathbb{E}_t^Q\left(D_{t+1}\right)$ are the true risk-neutral expected dividends in period $t+1$. We express the *hypothetical* price of replicating the futures contract as

$$\hat{F}_t = S_t \left(1 + \hat{r}_t{}^f\right) - \hat{\mathbb{E}}_t^Q\left(D_{t+1}\right), \tag{7}$$

where $\hat{r}_t{}^f$ is the benchmark financing rate and $\hat{\mathbb{E}}_t^Q\left(D_{t+1}\right)$ are the measured dividend expectations.

We define the futures-cash basis in period t as the difference between the price of a futures contract and the hypothetical price of replicating the futures contract, normalized by the spot price and the contract's time to maturity in years (denoted by m). This can be written as

$$\begin{aligned} Basis_t &= (S_t \times m)^{-1} \left(F_t - \hat{F}_t \right) \\ &= (S_t \times m)^{-1} \left((F_t - S_t) - (\hat{F}_t - S_t) \right) \\ &= \underbrace{\frac{1}{m} \left(r_t^f - \frac{\mathbb{E}_t^Q (D_{t+1})}{S_t} \right)}_{\text{Cost of Carry}} - \underbrace{\frac{1}{m} \left(\hat{r_t}^f - \frac{\hat{\mathbb{E}}_t^Q (D_{t+1})}{S_t} \right)}_{\text{Hypothetical Cost of Carry}} . \end{aligned} \tag{8}$$

As expressed in equation (8), the basis is equal to the cost of carry of a futures contract minus the hypothetical cost of carry. The scalar $1/m$ expresses the basis in annual terms.[12]

To compute the basis, we require data on dividend expectations, benchmark interest rates, and futures and spot prices. Data on risk-neutral dividend expectations are not systematically available for our sample. From January 2007 through the end of our sample, we use daily point-in-time forecasts of index dividends provided by Goldman Sachs as our measure of dividend expectations. The forecasts are constructed from dividend estimates for the index constituents and are provided as "dividend points," which are in units of the price level of the index. From 2000 through 2006, we use daily data on the realized dividends of an index from t to $t+1$ to proxy for dividend expectations. The basis that we measure includes a dividend "error term," which reflects the difference between the true risk-neutral expectation of dividends and our measure of expectations. These differences may stem from dividend risk premia, taxation of dividends, and measurement error. In Section II of the Internet Appendix, we extensively

[12]The cost of carry here is the negative scaled value of carry studied in Koijen, Moskowitz, Pedersen, and Vrugt (2018) across asset classes.

analyze the impact of this error term.[13] We find that it does not meaningfully contribute to our headline results. Additionally, in Section V below, we analyze the pricing of total return swaps, which provide a measure related to the basis that is not affected by measurement issues related to dividends. The analysis confirms that the dividend error term is not the primary driver of our results and has little impact.

We use the local interbank offered rate, measured daily and interpolated to match the maturity of the futures contract, as the benchmark interest rate. Dealers' actual financing rates may differ from the benchmark rate, due to balance sheet costs and other considerations such as securities lending. Put differently, our benchmark rate does not reflect all financing considerations for dealers. However, it is exactly the wedge created by these other financing considerations, which vary with the amount of futures demand that dealers face, that we are interested in capturing and studying.[14]

We use pricing data from Thompson Reuters Tick History (TRTH) to construct the basis. For spot index prices, the database contains the last traded prices of each index at a minute-by-minute frequency, aggregated from the last traded prices of the individual constituents in the index. For futures prices, the database contains tick-level data, which we use to compute minute-by-minute futures prices by taking the midpoint from the last bid and ask quotes. We aggregate the futures and spot prices to daily values by taking the mean across all minutes for which we have prices in both markets. Relative to using end-of-day pricing, this approach reduces estimation error and controls for asynchronous closing prices in futures markets and

[13] The Internet Appendix is available in the online version of the article on the *Journal of Finance* website.

[14] Our headline results remain the same using alternate benchmark rates, for example, overnight indexed swap rates. In Section IV of the Internet Appendix, we show that our headline results also persist in cross-sectional comparisons of indices with the same benchmark rate. Our results also have implications for other work that considers the interest rates embedded in derivatives prices (e.g., van Binsbergen, Diamond, and Grotteria (2022)), which we discuss in more detail in Section VI of the Internet Appendix.

cash equity markets.[15] We construct values of the basis at a daily frequency, using our data on prices, dividend expectations, and interest rates.

For each equity index, we construct a series that combines the basis of individual futures contracts with different expirations. We use the near contract until 10 days before expiration, where most of the trading takes place in this market. Within 10 days to expiration, we use a linear combination of the basis values of the nearest and second-nearest contracts, with the weight on the front contract transferring linearly to the back contract as the front contract nears maturity.[16]

C. *Cost of Carry and the Futures-Cash Basis*

To more clearly present our calculation of the futures-cash basis and illustrate some of the dynamics of the basis, in Figure 2 we zoom in on the period from January 2015 to December 2017 and plot daily values of the cost of carry, the hypothetical cost of carry, and the futures-cash basis for two indices: the S&P 500 and the Russell 2000.

The top panel of the figure plots the values for the S&P 500 index. The hypothetical and true cost of carry are negative on average, but rising at the end of the period, tracking the difference between interest rates and dividend yields in this period. The hypothetical cost of carry moves with the cost of carry, but not perfectly so. Both display some seasonal fluctuations, which correspond largely with the seasonality of dividends. The basis is positive on average, though it can and does become negative. It also displays occasional upwards or downwards spikes around quarterly futures expirations, which may be driven by a combination of scaling by maturity for

[15] For example, spot trading for S&P 500 index constituents ends at 4:00 PM, while futures markets close at 4:15 PM.

[16] This choice mitigates spikes in the basis around contract expirations, which are due to scaling by maturity and to trading around contract expirations. 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.

maturities close to zero and by the trading behavior of market participants "rolling" their futures positions (trading out of the nearest expiration contract and into the second-nearest expiration contract).

The bottom panel of the figure plots values for the Russell 2000 index. The values display similar properties as those of the S&P 500, though they are more volatile. Notably different is the fact that the basis is negative on average, though it is moderately positive in parts of 2016 and 2017. We further discuss this negative average value in the next section, which appears to be related to the fact that futures dealers tend to face substantial short demand in Russell 2000 futures.

–Figure 2 here–

D. Summary Statistics of the Basis

Table I reports summary statistics for the futures-cash basis in global equity markets. We report summary statistics for the full sample, as well as for two subsamples: January 2000 to June 2007, and July 2007 to December 2017. Panel A reports the average basis, average absolute value of the basis, and average time-series and cross-sectional standard deviations of the basis in annualized basis points.[17] For global equities, the average basis is -1 bp, but the average absolute value of the basis is 57 bps, the average time-series standard deviation is 92 bps, and the average cross-sectional standard deviation is 90 bps. These numbers suggest that the basis is close to zero on average, but there is substantial variation in the basis over time and across indices. The magnitude of and variation in the basis are slightly lower in the post-2007 period than in the pre-2007 period.

Panel B reports the average pairwise correlation of the futures-cash basis across the indices in our sample, both for the full sample and for the two sub-samples. Over the full sample, the

[17]We report asset-by-asset summary statistics of the basis in Internet Appendix Table IA.II, and we plot the basis for each index in Internet Appendix Figure IA.1.

average correlation of the basis across indices is 0.17; this value is higher in the second part of the sample (0.22) than in the first part of the sample (0.11). Because the indices in our sample trade asynchronously, we also report the average pairwise correlation of the three-day rolling average of the basis. The reported values are similar. For comparison, the last two columns of Panel B also report the average pairwise correlation of returns (0.53) and the three-day rolling average of returns (0.67). Panel C reports the average pairwise correlation of the basis across the U.S. indices in our sample. The average full-sample correlation is 0.57, and the average correlation is again higher in the second part of the sample (0.61) than in the first part of the sample (0.42). These numbers are higher than the international correlations, but are lower than the average correlation of returns across the U.S. indices (0.89 over the full sample).

Panels B and C suggest a positive correlation in the basis across indices, driven perhaps by correlated demand. There is also a substantial index-specific component to the basis, and the correlation of the basis is considerably lower than the correlation of returns across indices.

–Table I here–

III. Testing the Model Predictions

In this section, we test the three predictions of the model. We test the first prediction by analyzing the relationship between the basis and investor positions in futures contracts for U.S. indices for which we have futures position data. We test the second and third predictions regarding the relationship between the basis and returns using all of the global indices in our sample. We use the investor position data for the U.S. indices to test the corollaries to the second and third predictions.

A. *Prediction 1: The Relationship Between Futures Positions and the Basis*

The first prediction is that the futures-cash basis should be negatively related to the futures positions of futures dealers and positively related to the futures positions of end users (i.e., informed traders and liquidity traders).

To test this prediction, we use data on futures positions from the CFTC. For financial futures traded on U.S. exchanges, the CFTC publishes the Traders in Financial Futures (TFF) report every Thursday, which provides the aggregate long and short positions of investors categorized into four groups: Dealers/Intermediaries, Institutional Asset Managers, Levered Funds (which we refer to as hedge funds), and Other Reportables.[18] For equity index i and investor category c, we define net positions as:

$$\textit{Net Positions}_{i,c} = \frac{\textit{Long Positions}_{i,c} - \textit{Short Positions}_{i,c}}{\textit{Open Interest}_i}. \tag{9}$$

This signed measure captures whether investors in a given category are net long or short in aggregate, and scales their net positions by the open interest.[19]

Most trading in equity index futures occurs on exchanges, as opposed to over-the-counter. Net positions from the TFF report should therefore capture a substantial amount of the overall positions of investors in equity index derivatives. For our sample, we have data on futures positions for the S&P 500, S&P 400, DJIA, Russell 2000, and NASDAQ indices.

[18]These designations come from Form 40 filings completed by reportable traders, as mandated by the CFTC. Dealers/Intermediaries "tend to have matched books…[and] include large banks…and dealers in securities, swaps, and other derivatives." The Institutional designation includes "pension funds, endowments, insurance companies, mutual funds, and portfolio/investment managers whose clients are predominantly institutional," while Levered Funds include "hedge funds and various types of money managers." The Other Reportables category includes traders who "mostly are using markets to hedge business risk."

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

Before directly testing the first prediction, we provide additional color on the data. Figure 3 plots the time series of each of the position series for each equity index. With the exception of the Russell 2000, dealer positions are on average net negative over the sample period, while institutional and hedge fund positions are net positive (the opposite holds for the Russell 2000 in this sample period). For each index, dealers hold the largest net positions, which are negatively correlated with those of all other investor categories. Together with Figure 2, the figure also reveals that the basis tends to be positive when dealers face long futures demand (and hold short futures positions) and negative when dealers face short futures demand. In the S&P 500, dealers tend to hold short futures positions, but briefly hold a long futures position from mid-2015 through mid-2016; the basis is negative during this period, but is positive for the rest of 2015 through 2017. For the Russell 2000, dealers tend to hold a long futures position, and the basis is correspondingly negative (the sample average is -76 bps, as reported in Internet Appendix Table IA.II). Towards the end of 2017, dealers' net positions switch to being short futures, and the basis correspondingly becomes positive.

–Figure 3 here–

Table II reports the correlations of net positions across investor categories. Panel A reports the average correlation of net positions by investor type within each index. For example, the entry in the Dealer column and Institutional row represents the correlation between net positions of dealers and institutional investors calculated for each index and then averaged across the indices. The average within-index correlation of dealer and institutional net positions is -0.66. Similarly, the average correlation of dealer and hedge fund net positions is -0.68, and the average correlation of dealer and other net positions is -0.28. The strong negative relationship between dealer positions and positions of other types of investors is consistent with dealers taking the other side of the futures demand of end users in equity markets.[20]

[20]Customer demand may alleviate dealer balance sheet constraints, if customers purchase assets that dealers

Panel B of Table II reports the average pairwise correlation of net positions by investor type across indices. For example, the entry in the Dealer row and Dealer column corresponds to the average pairwise correlation of net positions of dealers in one index with dealer positions in the other indices, averaged across all indices. On average, dealer positions have a correlation of 0.36 across indices. For other investors, positions are correlated across indices, with the strongest correlation for hedge funds (0.39). Panel B of Table II suggests a channel through which the basis is correlated across indices: the correlation between dealer (and customer) positions. However, like the basis, positions also exhibit a strong index-specific component.

–Table II here–

We test the relationship between dealer positions and the basis by running a panel regression of the annualized futures-spot basis on dealer net positions. Table III shows a strong negative relationship between dealer net positioning and the basis. The coefficient on dealer positions (which is scaled to mean zero and unit variance) is strongly significant, with a t-statistic of -3.74 (column (1)). Adding entity and time fixed effects reduces the coefficient but continues to yield a strong and significant negative relationship. The negative relationship holds both in the cross-section (at a given time, indices with more negative dealer positions have more positive bases) and the time series (for a given index, when dealer positions are more negative, the basis is more positive). The regression coefficients suggest that a one-standard-deviation increase in dealer positioning corresponds to a decrease in the basis ranging from 28.9 bps (with no fixed effects) to 10 bps (with time and entity fixed effects). These findings are consistent with dealers facing increasing marginal costs for meeting additional futures demand, resulting in a futures-cash basis that increases with demand.

We next investigate the relationship between end-user positions and the futures-cash basis. We run multivariate regressions of the futures-cash basis on net positions by institutional in-

are holding. However, the persistent opposing signs of dealer and end user positions, together with the regression results, suggest that on average, customer demand induces dealers to expand their balance sheets.

vestors, hedge funds, and other reportables. The last four columns of Table III report the results. Across all specifications, institutional investor positions are significantly positively related to the futures-cash basis. A one-standard-deviation change in institutional investor positions leads to a 6.7 bp to 20.6 bp increase in the futures-cash basis, depending on the fixed effects specification. Hedge fund positions are also positively related to the basis, with a one-standard-deviation change in hedge fund positions corresponding to a 3.8 bp to 19.7 bp increase in the futures-cash basis. Other investor positions are also related to the basis, though the coefficients are smaller.

In Internet Appendix Figure IA.5, we report t-statistics from time-series regressions of the basis on the net futures positions of each investor category for each individual U.S. index. The negative relationship between the basis and dealers' futures positions, and the positive relationship between the basis and hedge fund and institutional investor futures positions holds for each of the five U.S. indices in our sample, providing further evidence in support of our story.

Overall, Table III shows that investor positions capture substantial variation in the futures-spot basis, explaining 26% of the variation over time and across markets without any controls and 69% of the variation together with time and entity fixed effects. The basis is strongly negatively correlated with dealer positions in futures, and strongly positively correlated with end user positions in futures, consistent with Prediction 1.

–Table III here–

B. Prediction 2: The Contemporaneous Relationship Between the Basis and Returns

The second model prediction is that changes in the basis are positively contemporaneously correlated with futures and spot market returns. We test this prediction by running a set of panel regressions of the form

$$r^{fut}_{i,t+1} = \quad a_i + b_{t+1} + c(Basis_{i,t+1} - Basis_{i,t}) + \epsilon_{i,t+1} \tag{10}$$

$$r^{spot}_{i,t+1} - r_{f,t} = \quad \alpha_i + \beta_{t+1} + \gamma(Basis_{i,t+1} - Basis_{i,t}) + \eta_{i,t+1}, \tag{11}$$

where $Basis^i_t$ is the futures-cash basis in market i measured in period t, r^i_{t+1} is the excess return of asset i from period t to period $t+1$, a^i is the asset-specific intercept (or fixed effect), b_{t+1} denote time fixed effects, and c and γ are the coefficients of interest that capture the contemporaneous relationship between the basis and returns. Regressions are estimated using weekly return data, in bps, where we scale the basis to have zero mean and unit standard deviation. Standard errors are clustered by asset and time.

Panel A of Table IV reports the results. Columns (1) to (4) display results for regressions in which the dependent variable is the futures return for a given market. Coefficients range from 47.4 with no fixed effects (t-statistic 5.25) to 18.0 with time and entity fixed effects (t-statistic 5.39). Columns (5) to (8) of report results for regressions in which the dependent variable is the spot return for a given market. Coefficients range from 43.2 with no fixed effects (t-statistic 4.99) to 13.7 with time and entity fixed effects (t-statistic 3.91). The coefficients indicate that a one-standard-deviation increase in the basis corresponds to a weekly futures return of 18 bps to 47 bps, and a weekly spot market return of 14 bps to 43 bps.[21] The smaller weekly spot market return of approximately 4 bps (or approximately 2% annualized) reflects the effect of the increasing basis.

[21]The cross-sectional standard deviation of changes in the weekly basis (averaged over time) is approximately 0.015 and the time-series standard deviation of changes in the weekly basis (averaged across indices) is approximately 0.017. For comparison, the cross-sectional standard deviation of weekly returns (averaged over time) is 1.46% and the time-series standard deviation of weekly returns (averaged across indices) is 2.81%. The more substantial time-series standard deviation of returns contributes to the difference in coefficients based on the fixed effect specification.

In Internet Appendix Figure IA.6, we report the t-statistics from contemporaneous time-series regressions of weekly futures and spot returns on changes in the basis for each individual index. The figure shows that the relationship between changes in the basis and futures and spot returns is positive for seventeen of the 18 indices in our sample, providing further evidence that the contemporaneous relationship between changes in the basis and returns holds across different equity markets.

Importantly, the sign of the relationship between futures market returns and the basis is the same as the sign of the relationship between spot market returns and the basis. The positive relationship between the basis and futures and spot market returns is consistent with a unique prediction of our model, namely that the basis captures futures demand that is also reflected in the spot market. Other theories of the futures-cash basis may predict no relationship between the basis and spot market returns, or may predict that the relationship should be opposite that with futures returns.

We also test the corollary to the second prediction, which holds that changes in dealers' (customers') futures positions should be negatively (positively) correlated with futures market and spot market returns. To test this corollary, we use the CFTC net futures positions data to run the regressions

$$r^{fut}_{i,t+1} = a_i + b_{t+1} + g(F^c_{i,t+1} - F^c_{i,t}) + \epsilon_{i,t+1} \tag{12}$$

$$r^{spot}_{i,t+1} - r_{f,t-1} = \alpha_i + \beta_{t+1} + \gamma(F^c_{i,t+1} - F^c_{i,t}) + \eta_{i,t+1}, \tag{13}$$

where $F^c_{i,t}$ is the net positions of investor category c at time t in index i. Changes in investor net positions are standardized to have zero mean and unit standard deviation (returns are in bps). Standard errors are clustered by entity and time.

Panel B of Table IV reports the regression results. We report results for specifications that include time and entity fixed effects. The first (last) four columns display results for regressions in which the dependent variable is futures (spot) market returns. The results suggest that a one-standard-deviation increase in futures dealer positioning corresponds to a -15 bp weekly futures market return (t-statistic -3.16) and a -14 bp weekly spot market return (t-statistic -3.08). Turning to end-user positions, the results suggest that a one-standard-deviation change in institutional investor positions corresponds to a 15 bp weekly futures return (t-statistic 7.14) and a 14 bp weekly spot market return (t-statistic 6.99), and a one-standard-deviation change in hedge fund positions corresponds to a 7 bp weekly futures return (t-statistic 1.54) and a 7 bp weekly spot market return (t-statistic 1.45).

Because independent variables in the regressions are standardized to have zero mean and unit standard deviation, the coefficients on futures positions in Panel B are directly comparable to the coefficients reported in Panel A with time and entity fixed effects (columns (4) and (8)). The 14 bp to 15 bp weekly return corresponding to a one-standard-deviation change in dealer positions is similar to the 14 bp to 18 bp weekly return corresponding to a one-standard-deviation change in the basis. For context, the average weekly return for all indices in the sample is approximately 11 bps, and the average weekly return of the U.S. indices over the period for which we have position data (2006 to 2017) is about 20 bps. Hence, the magnitude of the relationship between futures positions, the basis, and returns is economically large.

These results, together with the evidence for Prediction 1, support the mechanism through which changes in the basis are contemporaneously related to futures and spot market returns. In particular, the basis captures demand for futures market exposure from customers, which is intermediated by futures dealers. Increases in the basis and more negative dealer futures positions capture increased futures demand, which corresponds to rising futures and spot market prices.

–Table IV here–

C. Prediction 3: The Predictive Relationship Between the Basis and Returns

The third prediction of the model is that the basis should negatively predict subsequent spot and futures returns. To test this prediction, we run the panel regressions

$$r_{i,t+1}^{fut} = a_i + b_{t+1} + cBasis_{i,t} + \epsilon_{i,t+1} \tag{14}$$

$$r_{i,t+1}^{spot} - r_{f,t} = \alpha_i + \beta_{t+1} + \gamma Basis_{i,t} + \eta_{i,t+1}, \tag{15}$$

where r_{t+1}^{i} is the return of asset i, a_i and α_i are asset-specific intercepts, b_{t+1} and β_{t+1} are time fixed effects, and $Basis_{i,t}$ is the futures-cash basis for asset i measured in the previous period. The coefficients c and γ capture the predictive relationship between the basis and subsequent returns. Regressions are estimated using weekly return data, in bps, where we scale the basis to be in bps per week. Standard errors are clustered by asset and time.

Panel A of Table V reports the results. Columns (1) to (4) report results when the dependent variable is the futures return for a given market. Coefficients in the futures market regressions range from -5.1 with no fixed effects (t-statistic -3.42) to -3.8 with time and entity fixed effects (t-statistic -4.21). Columns (5) to (8) report results when the dependent variable is the spot return for a given market. Coefficients in the spot market regressions range from -3.5 with no fixed effects (t-statistic -2.50) to -2.2 with time and entity fixed effects (t-statistic -2.14). The regression coefficients suggest that for a basis of 10 bps per week, the subsequent week's futures returns are 38 to 51 bps lower and the subsequent week's spot returns are 22 to 35 bps lower.

The significant negative relationship between the basis and the subsequent week's futures and spot returns is consistent with our liquidity demand-based explanation for the futures-cash basis. The unique part of this prediction is that the basis forecasts futures market returns and spot market returns *with the same sign*, which is borne out in the data.

The variables in the regression are scaled such that the basis converging to zero, without any additional return effects, would coincide with $-1 \leq \gamma \leq 0$, $0 \leq c \leq 1$, and $c - \gamma = 1$, where c is the regression coefficient on spot market returns and γ is the regression coefficient on futures market returns. However, futures prices move four to five times more than predicted by futures converging to zero, while spot prices move in entirely the opposite direction.[22] The evidence points to futures prices and spot prices responding to forces beyond convergence.

In Internet Appendix Figure IA.7, we show t-statistics from predictive time- series regressions of weekly futures and spot returns on the lagged basis for each individual index separately. The figure shows that the relationship between the basis and subsequent futures and spot market returns is negative for 14 of the 18 indices in our sample, providing evidence that the negative predictability of the basis occurs in the majority of indices in our sample.

To shed additional light on the mechanism, we test the corollary to the third prediction, which holds that dealers' futures positions should positively predict subsequent futures and spot returns, and that customers' futures positions should negatively predict subsequent futures and spot returns. Using CFTC investor net positions data, we run the panel regressions

$$r^{fut}_{i,t+1} = a_i + b_{t+1} + gF^c_{i,t} + \epsilon_{i,t+1} \tag{16}$$

$$r^{spot}_{i,t+1} - r_{f,t} = \alpha_i + \beta_{t+1} + \gamma F^c_{i,t} + \eta_{i,t+1}, \tag{17}$$

where $F^c_{i,t}$ is the net positions of investor category c in index i at time t. Investor net positions are normalized to have zero mean and unit standard deviation (returns are in bps). Standard errors are clustered by entity and time.

Panel B of Table V reports the results with time and entity fixed effects. A one-standard-

[22]We note that $c - \gamma$ is not exactly equal to one in the regressions, as we may expect. This is due to a slight mismatch between how futures returns are measured (using daily settlement prices for the nearest-to-expiration futures contract) and how the basis is measured (a linear combination of the basis computed using average minute-by-minute prices for the nearest- and second-nearest-to-expiration contracts when the nearest contract is within 10 days to expiration).

deviation change in weekly futures dealer positions corresponds to a 6.1 bp higher weekly futures markets return (t-statistic 3.52) and a 5.7 bp higher weekly spot market return (t-statistic 3.48) in the following week. Since the average weekly futures return for U.S. indices is about 20 bps, these numbers suggest that the relationship between dealer positions and returns is substantial. A one-standard-deviation change in institutional investor positions corresponds to a 3.6 bp lower weekly futures return (t-statistic -1.72) and a 3.2 bp lower weekly spot return (t-statistic -1.58) in the following week. A one-standard-deviation change in hedge fund positioning corresponds to a 6.7 bp lower weekly futures return (t-statistic -3.45) and a 6.5 bp lower weekly spot return (t-statistic -3.30) in the following week.[23]

The regression results provide further evidence that the basis captures liquidity demand for equity index exposure that is reflected in futures and spot markets, with return predictability reflecting compensation to liquidity providers for taking positions opposite customer demand.

–Table V here–

D. Quantifying the Basis Return Predictability with Trading Strategies

To quantify and better understand the return predictability of the basis suggested by Prediction 3, we construct trading strategies that take positions in each index based on its future-spot basis.

D.1. Cross-Sectional LMH Liquidity Demand Strategy

We construct a low-minus-high (LMH) liquidity demand trading strategy that goes long equity indices in which futures are "cheap" relative to their hypothetical spot-implied price and

[23]Due to the fixed effects, the results do not mean that hedge funds lose money on their futures positions. Hedge funds often trade on time-series momentum, which is highly profitable (Moskowitz, Ooi, and Pedersen (2012)). Rather, the results are consistent with the returns of an equity index being lower when hedge funds demand more futures on the index.

short equity indices in which futures are "expensive" relative to their hypothetical spot-implied price. We construct two versions of the strategy, one that trades exclusively in futures and one that trades exclusively in the spot market. Positive returns to the strategies would suggest that indices in which futures that appear cheap outperform indices in which futures appear expensive.

We follow Koijen, Moskowitz, Pedersen, and Vrugt (2018) and form portfolios of indices weighted in proportion to the cross-sectional rank of their basis. The weight on index i at time t, and the portfolio returns in period $t+1$, are given by

$$w_t^i = \kappa_t \left(\text{rank}\left(-X_t^i\right) - \frac{N_t + 1}{2} \right) \tag{18}$$

$$R_{\text{LD,t+1}} = \sum_{i=1}^{N_t} w_t^i \tilde{r}_{i,t+1}, \tag{19}$$

where N_t is the number of available indices at time t, the scalar κ_t ensures that the sum of the long and short positions equals \$1 and \$$-1$, respectively, X_t^i is the signal used to form the portfolio, and $R_{LD,t+1}$ is the return at time $t+1$ of the LMH liquidity demand portfolio.[24] In the main specification, X_t^i is the one-day lagged basis for index i at time t, and we form portfolios on Friday of each week. In additional robustness tests, we further lag values of the basis to sort portfolios, and use different portfolio rebalancing frequencies.[25]

[24]This is similar to the weighting scheme employed by Asness, Moskowitz, and Pedersen (2013), who show that the resulting portfolios are highly correlated with other zero-cost portfolios that use different weights.

[25]In Section V of the Internet Appendix, we construct alternative global equity LMH strategies excluding the U.S. indices. The resulting portfolios are highly correlated with our baseline specification and realize similar performance.

D.2. *Time-Series LMH Liquidity Demand Strategy*

To study the time-series return predictability of the basis, we construct a timing strategy where the weight of security i is given by

$$w_{i,t} = z_t \left(-2\mathbb{I}\left(X_{i,t} - \bar{X} > 0\right) - 1\right). \tag{20}$$

In Equation (20), X_i^t is the basis of asset i, $\bar{X}_i$ is the mean of that basis (estimated using information up to time $t-1$), and $\mathbb{I}(X_t^i - \bar{X}_i > 0)$ is an indicator function that equals one if $X_t^i > \bar{X}_i$. We set z_t such that we have \$2 of exposure in each period, although instead of being \$1 long and \$1 short at all times, the strategy typically takes aggregate long or aggregate short positions.

D.3. *LMH Liquidity Demand Trading Strategy Returns*

Table VI reports the annualized mean, standard deviation, skewness, excess kurtosis, and Sharpe ratio of the returns to the cross-sectional LMH portfolio ("LMH Liquidity Demand XS") and the timing portfolio ("LMH Liquidity Demand TS"). Panel A reports statistics for the main specification, which are weekly rebalanced strategies, and Panel B for strategies that are rebalanced monthly. For comparison, we also report statistics for cross-sectional and timing reversal strategies, common proxies for the returns to liquidity provision (Jegadeesh (1990), Nagel (2012), and Drechsler, Moreira, and Savov (2021)). Panel A reports statistics for one-week reversal strategies rebalanced at the end of each week, and Panel B for one-month reversal strategies rebalanced at the end of each month.

Panel A shows that the annualized Sharpe ratio of the cross-sectional LMH portfolio is 0.86 in the futures market and 0.62 in the spot market, while the annualized Sharpe ratio of the timing portfolio is 0.69 in the futures market and 0.54 in the spot market. The performance of the strategies is of similar magnitude as the performance of the one-week reversal strategies formed in our sample. We find no evidence of negative skewness for the strategies, but some evidence of excess kurtosis.

Panel B shows that the performance of the LMH liquidity demand strategies persists, even at lower rebalancing frequencies. The Sharpe ratio of the monthly rebalanced cross-sectional LMH portfolio is 0.84 when implemented in the futures market and 0.72 when implemented in the spot market. The monthly-rebalanced timing LMH portfolio has a Sharpe ratio of 0.37 when implemented in the futures market and 0.30 when implemented in the spot market. These results stand in contrast to the more substantial decay in the performance of reversal strategies as we move to the monthly frequency. The cross-sectional reversal strategies rebalanced monthly have lower Sharpe ratios of 0.50 (futures) and 0.45 (spot). The monthly timing reversal strategies have Sharpe ratios of -0.22 (futures) and -0.24 (spot), consistent with equity indices exhibiting one-month continuation in the time series, as documented by Moskowitz, Ooi, and Pedersen (2012). The evidence suggests that the LMH strategies capture a distinct dimension of liquidity demand and supply not captured by short-term past price changes.

The returns to the trading strategies are substantial when implemented in the spot market, though they do not earn the same basis profitability as the strategies implemented in the futures market. With weekly rebalancing, in the cross-sectional strategy, the annualized average return of the strategy trading in futures (spot) is 7.21% (5.22%) per year. The difference between the two, 1.99%, is the amount that can be attributed to profitability accrued from basis convergence. The results suggest that the vast majority of the profitability of the LMH liquidity demand strategy returns occur in the spot market.

–Table VI here–

Figure 4 plots the cumulative returns of the LMH trading strategies. The strategies earn consistently strong returns in the first part of the sample (January 2000 through December 2006) as well as the second part (January 2007 through December 2017). In the first part of the sample, the LMH cross-sectional strategy earns a Sharpe ratio of 0.80 (0.50) in the futures (spot) market and the LMH timing strategy earns a Sharpe ratio of 0.69 (0.45) in the futures (spot) market. In the second part of the sample, the cross-sectional strategy earns a Sharpe ratio of 0.91 (0.74) in the futures (spot) market and the timing strategy earns a Sharpe ratio of 0.70 (0.60) in the futures (spot) market.

–Figure 4 here–

E. Further Analysis of Trading Strategies

The trading strategies provide strong evidence consistent with the third prediction of the model, that the basis negatively predicts returns in futures and spot markets. In Section VII of the Internet Appendix, we further examine the basis trading strategies to better understand the return predictability of the basis. The returns of the strategies are not explained by exposure to other well-known return predictors (e.g., value, momentum, carry, time-series momentum, and short-term reversals). We also find that the strategies' returns are driven in particular by time-varying (rather than static) variation in the basis across indices and idiosyncratic (rather than systematic) variation in the basis over time. The holding-period returns of the strategies are concentrated within a month, consistent with the degree of persistence of the basis and in dealer net positions in futures. Lastly, somewhat surprisingly, the trading strategies are only weakly exposed to funding liquidity and volatility shocks. This result is explained in prt by the fact that hedge funds appear to play the role of liquidity demanders rather than liquidity suppliers in futures markets, as captured by the basis, and they reduce their equity index futures positions when funding conditions deteriorate.

IV. Futures and Spot Market Liquidity Demand

A key component of our story is that liquidity demand in futures markets, as captured by the basis, is highly correlated with demand faced by liquidity providers in the spot market. We more closely examine this assumption by studying the relationship between the basis, futures positions, and flows into funds that are benchmarked to the U.S. indices in our sample.[26]

We obtain data on daily net flows and fund sizes for U.S. open-end funds and ETFs for the period 2007 to 2017 from Morningstar Direct, for all funds for which data are available at a daily frequency. We construct a weekly proxy for flow-based demand for each of the five U.S. indices in our sample as the sum of all weekly net flows into funds that list the index as a benchmark on their prospectus, normalized by the lagged sum of the net assets of those funds. The logic behind this measure is that open-end funds and ETFs purchase shares in their benchmark index in response to flows, corresponding to spot market liquidity demand for the index.

We run panel regressions of weekly changes in the five-day rolling average of the basis on the flow-driven demand measure, which we standardize to have mean zero and unit standard deviation. A positive coefficient corresponds to the basis of an index increasing in weeks in which that index receives inflows. Panel A of Table VII reports the results, which are all statistically significant, with t-statistics ranging from 4.08 to 4.22. A one-standard-deviation change in weekly flows corresponds to a 1.9 to 2.7 bp increase in the weekly basis (which has a standard deviation of 30 bps). This relationship is consistent with spot market liquidity providers facing direct spot market demand at the same time that customers demand futures, as reflected in the basis.

We next run panel regressions of the weekly changes in futures positions on the flow-driven demand measure. Panel B of Table VII reports results of regressions in which the dependent variable is the change in dealer net positions. As before, we standardize the position variables to have zero mean and unit standard deviation, which implies that the coefficients can be broadly

[26]Other work documents the effects that flow-induced price pressure may have on individual stock returns, for example, Coval and Stafford (2007), Lou (2012), and Khan, Kogan, and Serafeim (2012). Related, Brown, Davies, and Ringgenberg (2021) explore mispricing from nonfundamental demand in ETFs.

interpreted as correlations. The coefficients range from -0.15 (t-statistic -3.85) with time and entity fixed effects to -0.25 (t-statistic -4.93) with time fixed effects only. The results suggest a strong negative relationship between dealer positions and mutual fund flows, indicating that the demand that dealers face in the futures market is highly correlated with flows into ETFs and open-end funds. Panels C and D report results from panel regressions in which the dependent variables are changes in hedge fund and institutional investor net positions. The relationship between weekly flows and changes in the positions of hedge funds is highly significant, with the coefficients ranging from 0.15 (t-statistic 3.94) with time fixed effects to 0.24 (t-statistic 7.43) with entity fixed effects. None of the regression coefficients on the flow-based measure is statistically significant in the institutional investor position regressions, although the coefficients are consistently positive. The evidence suggests that our flow-based demand variable captures demand for futures from hedge funds and other levered investors, but not necessarily demand from institutional investors. The institutional investor category is defined by the CFTC to include pension funds, endowments, and insurance companies, whose liquidity needs in futures may be different.

The relationship we identify between the basis, investor positions, and fund flows can operate through two channels, both of which are consistent with liquidity demand. Under the first channel, which we believe is likely the dominant one, hedge funds simultaneously use futures, ETFs, and index funds as vehicles to rebalance their equity index exposure. The use of all three types of instruments results in common demand that is reflected in fund flows, the basis, and hedge fund futures positions, consistent with the mechanism captured by our model. Under the second channel, open-end funds and ETFs facing inflows themselves use futures to rebalance their market exposure, although this effect is likely considerably smaller.

The relationship between flows, the basis, and investor positions supports the assumptions of our model, and suggests that demand for futures is correlated with direct demand for equity index exposure faced by liquidity providers in the spot market. The evidence thus supports the view that demand for equity index exposure plays an important role in the basis and its return predictability.

–Table VII here–

V. Dealer Costs and the Futures-Cash Basis

In this section, we more closely study dealer costs, which also play a crucial role in our story, as they enable futures demand to show up in the futures-cash basis. First, we analyze the relationship between the futures-cash basis and the pricing of total return swaps, which provide a direct measure of the all-in costs that dealers in equity index markets face to provide leverage. Second, we study a mechanism through which dealers' marginal costs to meet futures demand for an index are increasing in demand for that index through the equity repo market. Third, we focus on the cost of balance sheet space by relating the futures-cash basis to other near-arbitrages that are also affected by the cost of balance sheet space.

A. Dealer Costs from Equity Total Return Swaps

We argue that the futures-cash basis is driven by the costs that dealers face to meet futures demand. We provide additional support for this story by analyzing indicative midprice quotes of three-month maturity equity index total return swaps from 2011 through the end of our sample for a subset of the indices in our sample. We obtain these data from an anonymous active market participant.

An equity total returns swap (TRS) is an agreement between two parties whereby one party receives the total returns of an equity index (which includes price changes and dividends) and pays a floating amount that is a benchmark interest rate plus a spread. TRS prices are quoted in terms of this spread. Because total returns include dividends, total return swaps do not have any dividend risk (unlike the futures-cash basis). TRS prices therefore provide a direct measure of the costs that dealers face to provide leveraged equity exposure in an equity index, including the cost of balance sheet space and the cost of financing positions in the index in the spot market. This feature of total return swaps makes them especially useful for dealers and other market participants to share financing costs and risks associated with their equity index derivatives businesses.[27]

Panel A of Table VIII reports the average and average absolute TRS quotes, as well as the same values for the futures-cash basis for the time period in which we have TRS pricing. The average absolute TRS quote is 35 bps versus 37 bps for the futures-cash basis, indicating that the magnitude of the quotes is similar to the magnitude of the basis. The average TRS quote is 28 bps versus 15 bps for the future-cash basis, indicating that the TRS quotes are slightly more positive than the basis on average. The panel also reports daily correlations between the TRS quotes and our measured basis values. The average correlation across indices is 0.49, with correlations as high as 0.73 (the S&P 500 and NASDAQ indices) and 0.77 (the DJIA index). We do not expect TRS quotes to be perfectly aligned with the basis for a variety of reasons, which include the maturity mismatch between the swaps and futures that we use to measure the basis, the fact that the basis captures traded market prices averaged over the course of a day versus TRS prices, which are indicative quotes to execute large notional trades provided by a single market participant in an over-the-counter market, and potential measurement differences stemming from treatment of dividends in the construction of the basis. The strong degree of commonality between the TRS quotes and the basis indicates that the basis captures the same costs associated with leveraged equity index exposure that are captured by TRS quotes capture.

Panel B of Table VIII reports Sharpe ratios for weekly rebalanced LMH cross-sectional

[27] One particular use of total return swaps is to hedge financing risks stemming from exotic derivatives businesses. Dealers often trade in exotic equity index derivatives with maturities longer than those of listed futures (e.g., 5 to 10 years), which makes swaps useful. While total return swaps have traded primarily over-the-counter, in recent years listed total return futures for various maturities have begun to trade for U.S. and European indices.

and timing strategies formed using TRS quotes as the sorting variable. For comparison, the panel also reports the same statistics for the LMH trading strategies sorted on the basis, formed over the same period using indices for which we have TRS quote data. The panel indicates that TRS quotes capture most of the return predictability associated with the basis. Trading strategy performance is nearly identical for timing strategies, while the basis appears to have slightly stronger cross-sectional return predictability. Given TRS quotes directly proxy for dealer financing costs for an equity index, the evidence supports the role that financing frictions play in giving rise to the basis and its return predictability, and helps mitigate concerns about other factors driving our results.

–Table VIII here–

B. Equity Repo and Securities Lending

Our model assumes that futures dealers face increasing marginal costs to intermediate additional futures demand in an index. Evidence justifying this assumption is that dealers prefer to obtain financing by using their hedge positions as collateral to borrow cash via repurchase agreements, or, alternatively, prefer to lend shares in their hedge positions in exchange for cash. The former is referred to as *equity repo*, while the latter is referred to as *securities lending*. The two are tightly linked. When dealers face additional long futures demand, these financing transactions lead them to increase the supply of shares available to borrow for an index. Holding fixed demand to borrow shares in the index, this corresponds to decreased interest benefits (a higher repo rate) from using the shares as collateral. Note that a primary purpose of securities borrowing is for shorting – if shorting demand in the spot market increases with short futures demand (and decreases with long futures demand), the effect that we describe is stronger. The behavior of equity repo rates is one mechanism through which marginal dealer financing costs are increasing in the amount of futures demand being intermediated.

The use of equity repo by dealers means that the benchmark financing rate used to price futures should be an equity repo rate, akin to the use of Treasury repo rates in bond futures pricing.[28] As a result, practitioners occasionally refer to the futures-cash basis in equity index futures, as well as the spread in total return swaps, as the *implied repo rate*.[29] However, unlike for cash bonds, historical data on the true "repo rates" for equity indices are not readily available. Accordingly, we are only able to construct imperfect proxies using data on average lending fees in securities lending markets. Importantly for our story, however, the equity repo rate for an index decreases as futures demand for that index increases, corresponding to the increased supply of securities for borrowing provided by dealers.

We use the Markit Securities Finance (MSF) Buy Side Institutional data set, which contains daily data on stock loans aggregated from a variety of market participants. From May 2007 onwards, the MSF data set provides data on the security lending fees for stocks. Average lending fees are a proxy for the marginal benefit from lending shares, which is directly related to equity repo rates and dealer financing costs. Using the data, we construct an index-level measure of security lending fees at each point in time by using the weight of each security in each index and data on security lending fees. We discuss the data and outline the procedure for this construction in Section VIII of the Internet Appendix.

Panel A of Table IX reports regression results for regressions of the futures-cash basis and TRS quotes on index security lending fees. Observations are five-day rolling averages sampled weekly, and standard errors are clustered by entity and time. Given that higher securities lending fees make it cheaper for dealers to provide long leverage, we expect the coefficients in the regressions to have negative signs. Focusing on regressions in which the basis is the independent variable, the coefficients in the regressions are all negative and range from -0.13

[28]Calculating the implied financing in bond futures involves the additional complication that bond futures have embedded delivery options, as market participants can choose which bond to deliver and the timing of delivery. This optionality is not present in the cash-settled equity index futures we study.

[29]For an example, see Heath (2017).

(with time and entity fixed effects) to -0.50 (with no fixed effect). The regressions suggest that securities lending fees have some explanatory power for time-series variation in the basis (t-statistics -2.07 and -2.23 with no fixed effects and with entity fixed effects, respectively), but have more limited ability to explain variation in the basis across indices. Focusing on regressions in which TRS quotes are the independent variables, the coefficients range from -0.15 (with time and entity fixed effects) to -0.24 (with entity fixed effects). Here, lending fees have slightly stronger explanatory power, with t-statistics greater 2 in all specifications except that with entity fixed effects (t-statistic -1.78), indicating that lending fees capture some cross-sectional and time-series variation in TRS quotes.

Panel B of Table IX reports regression results for dealer futures positions on five-day rolling average index security lending fees. Observations are sampled weekly and standard errors are clustered by entity and time. Dealer futures positions are standardized to have zero mean and unit standard deviation and security lending fees are in percentage points. Regression coefficients range from 0.30 (with time and entity fixed effects) to 2.50 (with no fixed effects), indicating that a 10 bp increase in the security lending fee corresponds to a 0.03 to 0.25 standard deviation increase in dealer positions, where t-statistics are equal to 3.78, 4.02, and 2.71 with no fixed effects, time fixed effects, and entity fixed effects, respectively, but fall to 0.41 when including time and entity fixed effects. The regression results indicate that securities lending fees tend to be higher in indices and time periods in which dealers face less long demand, consistent with the mechanism we propose.

Our results suggest a relationship between the basis, futures positions, and security lending fees consistent with securities lending/equity repo serving as a strategy for dealers to obtain financing for their hedge positions. While there is a relationship in the data, there is also substantial variation in the basis and in dealer futures positions not captured by securities lending fees. Hence, other factors may help explain why dealer financing costs for an index increase with demand for that index, for example, risk management and trading position limits.[30]

–Table IX here–

C. Bank Balance Sheet Costs and Other Pricing Deviations

Another important component of the basis in our model is C_t, which dealer financing costs associated balance sheet space. The term C_t is high in periods when dealers face high balance sheet costs (e.g., because of leverage constraints) and low in periods when they are less constrained. Given many of the same intermediaries operate across asset classes, in periods in which C_t is high, we expect large pricing deviations to occur *across* asset classes. Here, we proxy for time-variation in C_t by focusing on the magnitude of pricing deviations across different markets, which provides color on the role of financing costs, as well as novel evidence for the relationship between the basis and pricing deviations in other asset classes.[31]

We construct two arbitrage indices to proxy for C_t. The first, which we call the equity arbitrage index, is constructed by taking the average absolute value of the basis for the non-U.S. equity indices in our sample at each point in time and standardizing the resulting series to have zero mean and unit standard deviation in our sample. The second is a fixed-income arbitrage index, which is constructed by taking the average of two series, each standardized to have zero mean and unit standard deviation in our sample: i) the average magnitude of three-month LIBOR-based deviations from covered interest rate parity for G10 currencies versus the U.S. Dollar, and ii) the 'Noise' measure of Hu, Pan, and Wang (2013), which captures

[30]For many large-cap stocks (e.g., those in the S&P 500), shares are easy to locate and borrow, and securities lending fees are low and do not vary substantially. The equity repo mechanism that we discuss here is likely to be important for a subset of the indices that we study, while for indices like the S&P 500, other factors likely play a more important role in explaining why dealer financing costs increase with demand.

[31]Other work shows that the magnitude of pricing deviations can capture intermediary balance sheet costs (e.g., Du, Hébert, and Huber (2021)). Our evidence is unique in illustrating the interactions between balance sheet costs, derivatives demand, and dealers' positions.

pricing deviations between one- to 10-year U.S. Treasury yields and a fitted yield curve.[32] We restandardize the fixed income arbitrage index to have zero mean and unit standard deviation in our sample.

We regress the futures-cash basis on the arbitrage indices, dealer net positions, and dealer net positions interacted with each arbitrage index. The coefficient of interest is the interaction term, which is the incremental slope of the relationship between dealer positions and the basis corresponding to a one-standard-deviation increase in the arbitrage index. Because dealer positions are negatively related to the basis, we expect the interaction term to have a negative sign.

The regression results are reported in Table X. Across all specifications, coefficients on dealer positions are similar to those coefficients reported in Table III (ranging from approximately 10 to 29), and are statistically significant at the 5% level. Columns (1) to (4) of the table report regression results using the equity arbitrage index as the interaction variable. Interaction coefficients range from -7.1 (with time and entity fixed effects) to -9.0 (with no fixed effects). Columns (4) through (8) report results using the fixed income arbitrage index as the interaction variable. Interaction coefficients range from -8.4 (with time and entity fixed effects) to -10.8 (with no fixed effects). Columns (9) to (12) report results when both arbitrage indices are interacted with dealer positions. Interaction coefficients on the equity arbitrage index range from -5.0 to -6.4, while the interaction coefficients on the fixed income arbitrage index range from -6.6 to -8.8. The magnitude of the regression coefficients is approximately 33% to 85% of the coefficient on dealer positions, indicating a substantial multiplier effect on the relationship between the basis and dealer positions. Interestingly, the two arbitrage indices appear to capture distinct but relevant information for the magnitude of the futures-cash basis in U.S. indices. In additional, the coefficients on the arbitrage indices themselves are statistically indistinguishable from zero, indicating as expected that their explanatory power comes from a

[32] Updated data on the *Noise* measure come from Jun Pan's website.

multiplier on dealer positions.

The regression results suggest that the average magnitude of pricing deviations from both international markets and other asset classes is useful for understanding the variation in the futures-cash basis. The basis reflects both the cost of balance sheet space, which is common to all assets, and asset-specific financing costs related to demand. The magnitude of pricing deviations across asset classes provides a useful proxy for variation in the cost of balance sheet space.

–Table X here–

VI. Conclusion

We show that violations of the law of one price convey more than just intermediation costs – they also provide information about liquidity demand in equity futures markets. Consistent with this view, we find that the basis between futures and spot prices negatively predicts returns in futures and spot markets *in the same direction*, distinct from futures market and spot market prices merely converging. The basis appears to capture futures demand from hedge funds and institutional investors, with the associated return predictability compensating liquidity providers for meeting this demand. Interestingly, while the properties of futures contracts, such as their embedded leverage, low transaction costs, and high liquidity, may make them seemingly ideal instruments for sophisticated traders to trade based on their information, our results suggest that futures contracts are often used by investors to meet their liquidity demands for equity market exposure.

Our results highlight the important role that supply and demand imbalances play in giving rise to violations of the law of one price, which may also be relevant in other asset classes. A previous version of this paper shows that deviations from covered interest rate parity in currency markets are related to hedging demand stemming from international capital flows. This relationship implies that deviations from covered interest rate parity contain information relevant for exchange rates, a point also made in Liao and Zhang (2020) and Greenwood, Hanson, Stein, and Sunderam (2022), with the latter also connecting the results to global bond markets. The supply and demand imbalance captured by the basis also has implications for interpreting the interest rates embedded in derivatives prices (e.g., as studied by van Binsbergen, Diamond, and Grotteria (2022)), which we discuss further in Section VI of the Internet Appendix. Our evidence suggests that in addition to reflecting financial frictions, the demand captured by deviations from the law of one price contains additional economic insights.

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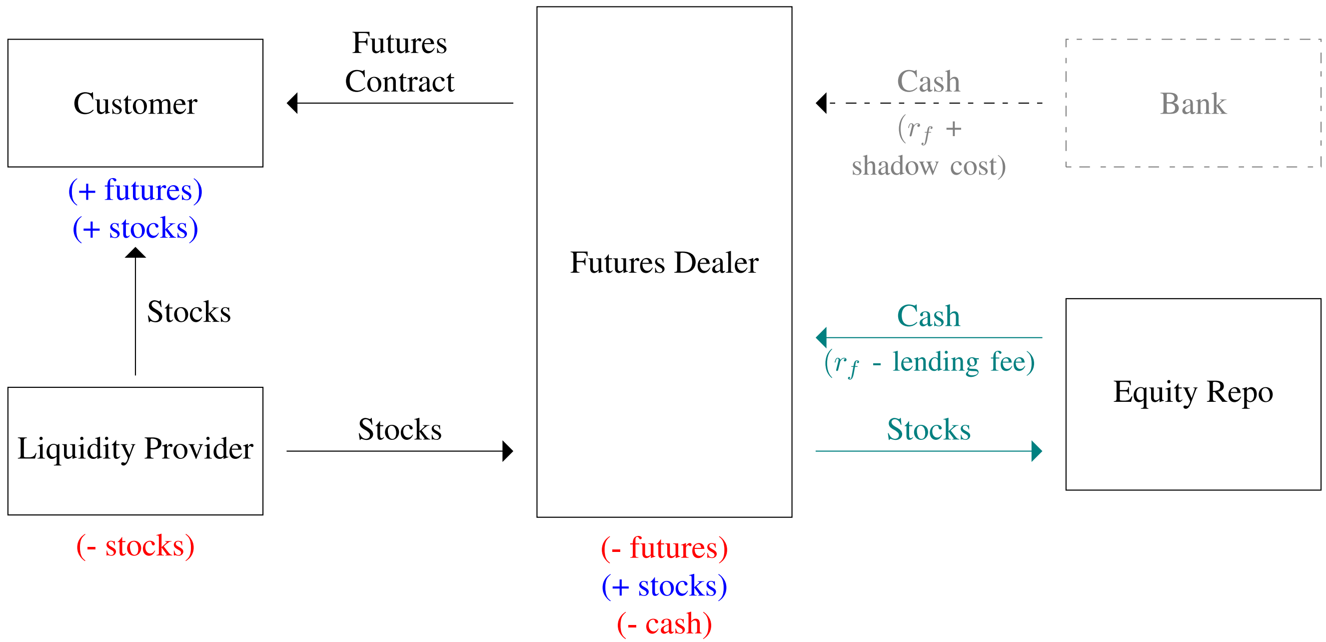
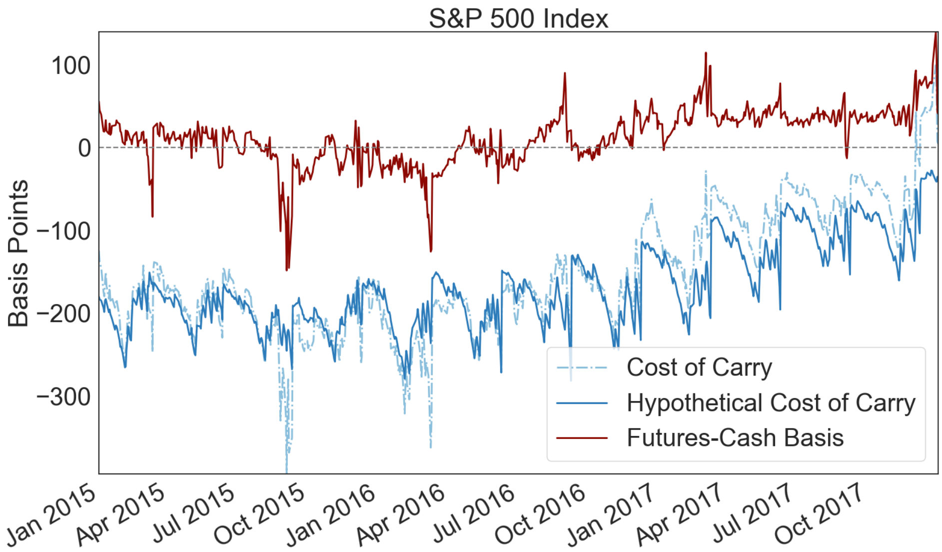


Figure 1. Mechanics of futures trading. The figure illustrates the mechanics of liquidity demand for equity index exposure. Customers demand both futures contracts and cash equities. Futures dealers meet the demand for futures, and hedge their equity market exposure by buying stocks. Dealers obtain financing for their hedge positions by lending out their stocks in exchange for cash, which provides a cheaper source of financing than uncollateralized borrowing (see Song (2016) for more discussion). Liquidity providers in the spot market meet both direct demand for stocks from customers, and hedging demand from futures dealers.



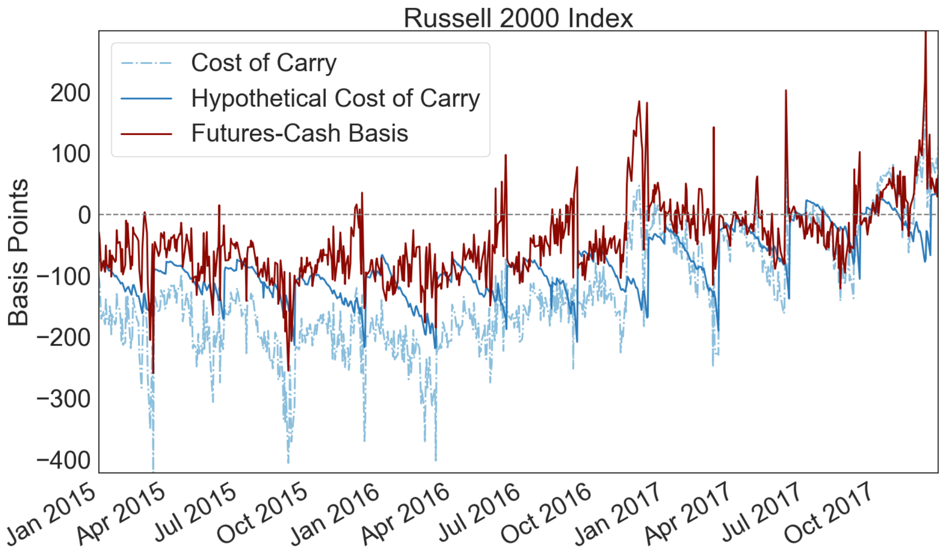


Figure 2. Cost of carry and the futures-cash basis. The figure plots the cost of carry, the hypothetical cost of carry, and the futures-cash basis for the S&P 500 index and the Russell 2000 index constructed using equation (8). All values are plotted from January 2015 through December 2017.

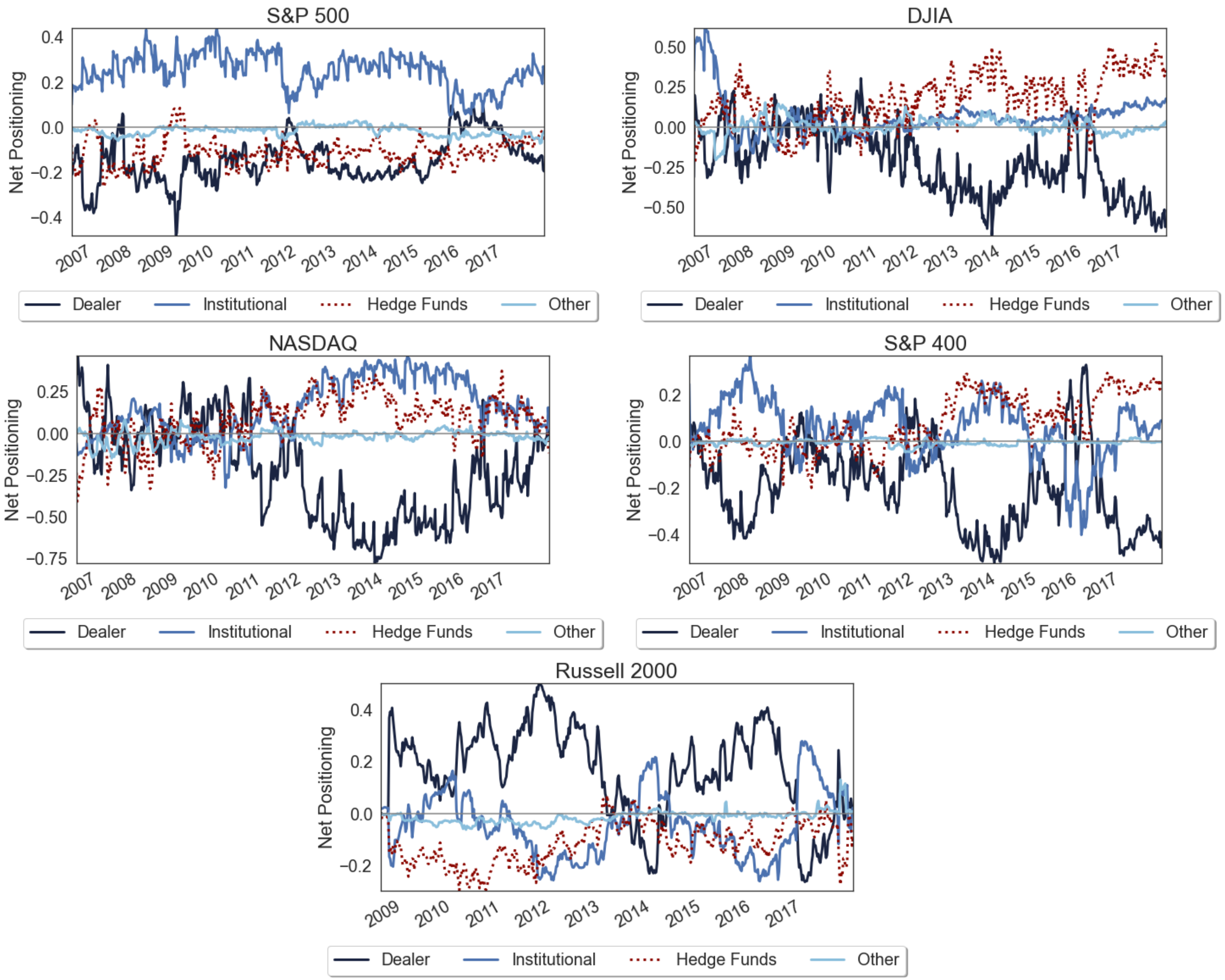
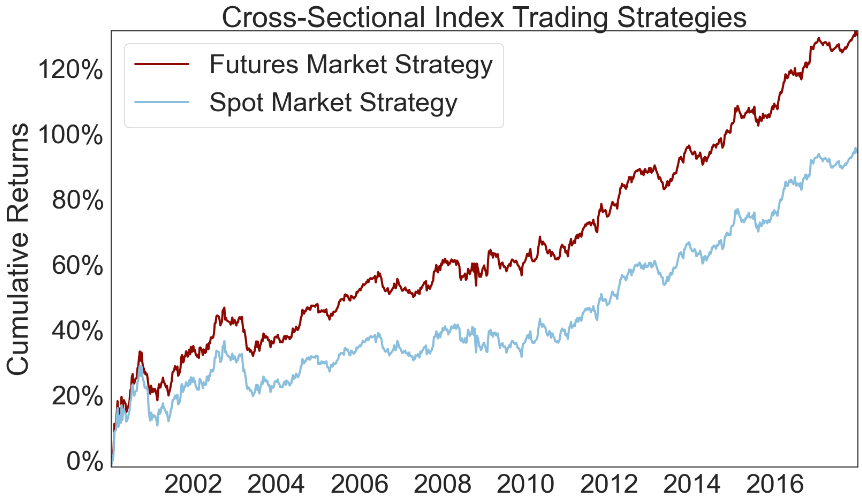


Figure 3. Net positions from the traders in financial futures report. The plots graph the ratio of the net number of contracts held by each investor type to the total open interest for a given equity index, as published in the weekly Traders in Financial Futures Report published by the CFTC. The report has been published in real time from 2010 to 2017, with the CFTC back-filling values from 2006 to 2010.



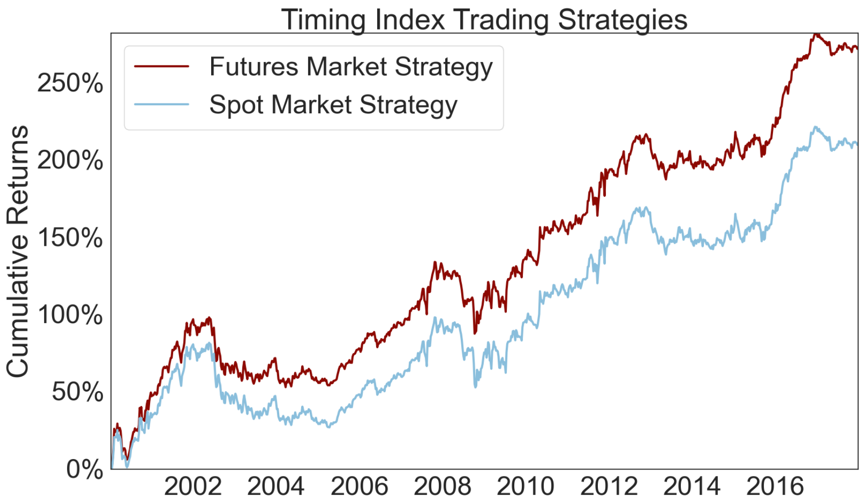


Figure 4. Trading strategy cumulative returns over time. The figure plots the cumulative returns of the weekly rebalanced LMH trading strategies. The top panel plots the returns of the cross-sectional LMH strategies, which take positions in indices weighted in proportion to the cross-sectional rank of their futures-cash basis, taking long positions in indices with more negative bases and short positions in indices with more positive bases. The bottom panel plots the returns of the LMH timing strategies, which take long positions in indices that have a more negative basis than their histories and short positions in indices that have a more positive basis than their histories. In each panel, the cumulative returns of the strategies implemented in futures contracts are in blue and the cumulative returns of the strategies implemented in the spot market are in red.

Table I
Basis Summary Statistics

The table displays summary statistics for the annualized basis in global equity markets. Panel A reports the average value of all basis observations in the sample, the average absolute value of all basis values in 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 period. Panel B displays the pairwise correlation of the basis and returns, as well as the pairwise correlation of the three-day rolling average of the basis and returns ("rolling pairwise"), averaged across all indices in the sample. Panel C displays the pairwise correlation of the basis and returns, as well as the pairwise correlation of the three-day rolling average of the basis and returns, averaged across the U.S. indices in the sample.

Panel A: Average Basis Values

	Average Basis	Average Absolute Basis	Average Basis TS-Stdev	Average Basis XS-Stdev
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

Panel B: Average Pairwise Correlations, All Indices

	Basis		Returns	
	Pairwise	Rolling Pairwise	Pairwise	Rolling Pairwise
Jan. 2000-Dec. 2017	0.17	0.19	0.53	0.67
Jan. 2000-Jun. 2007	0.11	0.09	0.48	0.62
Jul. 2007-Dec. 2017	0.22	0.24	0.57	0.70

Panel C: Average Pairwise Correlations, U.S. Indices

	Basis		Returns	
	Pairwise	Rolling Pairwise	Pairwise	Rolling Pairwise
Jan. 2000-Dec. 2017	0.57	0.60	0.89	0.89
Jan. 2000-Jun. 2007	0.42	0.37	0.86	0.87
Jul. 2007-Dec. 2017	0.61	0.65	0.91	0.91

Table II
Correlation of Net Positions by Investor Type

Net position 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 positions by 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 positions across investor types for each index. Panel B reports the average correlation of net positions for each investor type across indices. For example, the dealer/dealer component of the table represents the average time-series correlation of the net positions of dealers across each of the five indices.

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

	Dealer	Institutional	Hedge Funds	Other
Dealer	0.36	-0.20	-0.32	-0.07
Institutional		0.11	0.13	0.03
Hedge Funds			0.39	0.11
Other				0.01

Table III
Regression of the Futures-Cash Basis on Investor Net Positions in Futures

Net position 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 positions. Panel B reports results of a regression of the futures-cash basis on standardized institutional, levered, and other positions. The futures-cash basis is an annualized rate. Standard errors are clustered by index and time, with t-statistics in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	(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

Table IV
Contemporaneous Relationship Between the Basis and Returns

The table reports results from regressions of the form

$$r^{fut}_{i,t+1} = a_i + b_{t+1} + c(\Delta x_{i,t+1}) + \epsilon_{i,t+1}$$
$$r^{spot}_{i,t+1} - r_{f,t} = \alpha_i + \beta_{t+1} + \gamma(\Delta x_{i,t+1}) + \eta_{i,t+1},$$

where $r_{i,t+1}$ is the return of asset i from period t to period $t+1$, a^i is the asset-specific intercept (or fixed effect), b_{t+1} and β_{t+1} are time fixed effects, $\Delta x_{i,t+1}$ is the change in the variable x for index i from t to $t+1$, and c and γ are the coefficients of interest that measure the contemporaneous relationship between the independent variable and market returns. Panel A reports results for regressions in which the independent variable is the futures-cash basis. Panel B reports the results for regressions in which the independent variable is the net positions of investor categories. The regression in Panel B contains only the U.S. equity indices in the sample. Returns in both sets of regressions are scaled to be in bps. Independent variables in the regressions are scaled to have zero mean and unit standard deviation. Observations are sampled weekly. Standard errors are clustered by time and entity. t-statistics are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: Contemporaneous Relationship Between Returns and The Basis

	Futures Market Returns				Spot Market Returns			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔBasis$_{t+1}$	47.41***	17.95***	47.41***	17.95***	43.20***	13.68***	43.20***	13.68***
	(5.25)	(5.39)	(5.25)	(5.39)	(4.99)	(3.91)	(4.99)	(3.91)
R^2	0.03	0.71	0.03	0.71	0.02	0.71	0.02	0.71
Observations	15522	15522	15522	15522	15522	15522	15522	15522
Time FE	No	Yes	No	Yes	No	Yes	Yes	Yes
Entity FE	No	No	Yes	Yes	No	No	Yes	Yes

Panel B: Contemporaneous Relationship Between Returns and Futures Positions

	Futures Market Returns				Spot Market Returns			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta F^{\text{Dealer}}_{t+1}$	-14.59**				-13.76**			
	(-3.16)				(-3.08)			
$\Delta F^{\text{Institutional}}_{t+1}$		15.11***				14.27***		
		(7.14)				(6.99)		
$\Delta F^{\text{Hedge Fund}}_{t+1}$			6.97				6.56	
			(1.54)				(1.45)	
$\Delta F^{\text{Other}}_{t+1}$				-0.55				-0.37
				(-0.17)				(-0.12)
R^2	0.91	0.91	0.91	0.91	0.91	0.92	0.91	0.91
Observations	2852	2852	2852	2852	2852	2852.00	2852	2852
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Entity FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table V
Basis Return Predictability

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

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

$$r^{spot}_{i,t+1} - r_{f,t} = \alpha_i + b_t + \gamma x_{i,t} + \eta_{i,t+1},$$

where $r^i_{t:t+1}$ is the return of asset i from period t to period $t+1$, $x_{i,t}$ is the independent variable in market i measured in period t, a^i is the asset-specific intercept (or fixed effect), b_t are time fixed effects, and c and γ are the coefficients of interest that measure the predictive relationship between the independent variable and equity market returns. Panel A reports results for regressions in which the independent variable is the futures-cash basis, scaled to be in bps per week. Panel B reports the results for regressions in which the independent variable is the net position of different investor categories, scaled to have zero mean and unit standard deviation. Returns in both sets of regressions are scaled to be in bps. The regression in Panel B contains only the U.S. equity indices in the sample. Observations are sampled weekly. Standard errors are clustered by time and entity. t-statistics are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: Return Predictability of the Basis

	Futures Market Returns				Spot Market Returns			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Basis$_{t-1}$	-5.09***	-3.85***	-5.06***	-3.80***	-3.54**	-2.28**	-3.44**	-2.15**
	(-3.42)	(-4.30)	(-3.17)	(-4.21)	(-2.50)	(-2.32)	(-2.26)	(-2.14)
R^2	0.00	0.71	0.00	0.71	0.00	0.71	0.00	0.71
Observations	15649	15649	15649	15649	15649	15649	15649	15649
Time FE	No	Yes	No	Yes	No	Yes	No	Yes
Entity FE	No	No	Yes	Yes	No	No	Yes	Yes

Panel B: Return Predictability of Investor Net Futures Positioning

	Futures Market Returns				Spot Market Returns			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
F^{Dealer}_{t-1}	6.11**				5.66**			
	(3.52)				(3.48)			
$F^{\text{Institutional}}_{t-1}$		-3.59				-3.24		
		(-1.72)				(-1.58)		
$F^{\text{Hedge Fund}}_{t-1}$			-6.72**				-6.50**	
			(-3.45)				(-3.30)	
F^{Other}_{t-1}				1.93				2.07
				(1.17)				(1.29)
R^2	0.91	0.91	0.91	0.91	0.91	0.91	0.91	0.91
Observations	2879	2879	2879	2879	2879	2879	2879	2879
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Entity FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table VI
LMH Liquidity Demand Returns

The table reports the weekly mean excess return, annualized mean excess return, annualized standard deviation, skewness of returns, kurtosis of returns, and annualized Sharpe ratio of the LMH liquidity demand strategy returns. Panel A displays statistics for weekly rebalanced portfolios and Panel B displays statistics for monthly rebalanced portfolios. The table displays statistics corresponding to the cross-sectional LMH liquidity demand portfolios ("LMH Liquidity Demand XS") and the LMH liquidity demand timing portfolios ("LMH Liquidity Demand TS"), implemented via futures contracts and in the spot market. Panel A reports statistics for weekly rebalanced one-week reversal strategies (cross-sectional and time series) and Panel B reports statistics for one-month reversal strategies (cross-sectional and time series), all formed using the global equity indices in the sample.

Panel A: Weekly Rebalanced Strategies

		Weekly Mean	Annualized Mean	Annualized Standard Deviation	Skewness	Kurtosis	Annualized Sharpe Ratio
Futures Returns	LMH Liquidity Demand XS	0.14%	7.21%	8.40%	0.53	4.00	0.86
	LMH Liquidity Demand TS	0.29%	15.10%	21.79%	0.60	4.31	0.69
Spot Returns	LMH Liquidity Demand XS	0.10%	5.22%	8.36%	0.17	3.71	0.62
	LMH Liquidity Demand TS	0.22%	11.65%	21.48%	0.43	3.99	0.54
Futures Returns	1-Week Reversal XS	0.16%	8.07%	10.41%	0.62	3.36	0.78
	1-Week Reversal TS	0.33%	17.30%	32.12%	-0.43	9.14	0.54
Spot Returns	1-Week Reversal XS	0.15%	7.60%	10.45%	0.64	3.61	0.73
	1-Week Reversal TS	0.33%	16.93%	31.94%	-0.38	8.71	0.53

Panel B: Monthly Rebalanced Strategies

		Weekly Mean	Annualized Mean	Annualized Standard Deviation	Skewness	Kurtosis	Annualized Sharpe Ratio
Futures Returns	LMH Liquidity Demand XS	0.49%	5.84%	6.97%	0.45	2.34	0.84
	LMH Liquidity Demand TS	0.53%	6.36%	17.06%	0.27	1.36	0.37
Spot Returns	LMH Liquidity Demand XS	0.42%	5.01%	7.01%	0.51	2.60	0.72
	LMH Liquidity Demand TS	0.43%	5.19%	17.08%	0.27	1.29	0.30
Futures Returns	1-Month Reversal XS	0.35%	4.25%	8.54%	0.43	2.70	0.50
	1-Month Reversal TS	-0.53%	-6.32%	28.44%	-0.16	2.35	-0.22
Spot Returns	1-Month Reversal XS	0.32%	3.89%	8.58%	0.52	3.14	0.45
	1-Month Reversal TS	-0.56%	-6.70%	28.24%	-0.13	2.25	-0.24

Table VII
Fund Flows, the Basis, and Investor Positions

The table reports statistics from panel regressions in which the dependent variable is the weekly flow into mutual funds and ETFs that list a given index as their benchmark. Panel A reports results from regressions in which the dependent variable is the one-week change in the five-day rolling average of the basis. Panel B reports results from regressions in which the dependent variable is the change in net positions of futures dealers. Panel C reports results from regressions in which the dependent variable is the change in net positioning of hedge funds. Panel D reports results from regressions in which the dependent variable is the change net positioning of institutional investors. All variables except the basis are standardized to have zero mean and unit standard deviation. t-statistics are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: The Basis and Flows

	(1)	(2)	(3)	(4)
Weekly Flows	2.69**	2.70**	1.86**	1.86**
	(4.08)	(4.10)	(4.22)	(4.22)
R^2	0.01	0.01	0.45	0.45
Observations	2812	2812	2812	2812
Time FE	No	No	Yes	Yes
Entity FE	No	Yes	No	Yes

Panel B: Dealer Positions and Flows

	(1)	(2)	(3)	(4)
Weekly Flows	-0.25***	-0.25***	-0.15**	-0.15**
	(-4.93)	(-4.91)	(-3.90)	(-3.85)
R^2	0.04	0.04	0.41	0.41
Observations	2713	2713	2713	2713
Time FE	No	No	Yes	Yes
Entity FE	No	Yes	No	Yes

Panel C: Hedge Fund Positions and Flows

	(1)	(2)	(3)	(4)
Weekly Flows	0.21***	0.21***	0.15**	0.15**
	(7.38)	(7.43)	(3.94)	(3.95)
R^2	0.03	0.03	0.35	0.35
Observations	2713	2713	2713	2713
Time FE	No	No	Yes	Yes
Entity FE	No	Yes	No	Yes

Panel D: Institutional Investors and Flows

	(1)	(2)	(3)	(4)
Weekly Flows	0.10	0.10	0.00	0.00
	(1.32)	(1.32)	(0.13)	(0.13)
R^2	0.01	0.01	0.41	0.41
Observations	2713	2713	2713	2713
Time FE	No	No	Yes	Yes
Entity FE	No	Yes	No	Yes

Table VIII
Total Return Swaps and the Futures-Cash Basis

The table reports statistics on indicative mid quotes for three-month term equity index total return swaps (TRS). The quotes are provided as spreads relative to benchmark interest rates, in annualized bps. Panel A reports the average value and average magnitude of daily TRS quotes, as well as the same values estimated for the futures-cash basis. The table also reports daily time-series corelations between the futures-cash basis and the TRS quotes, as well as the start date for which we have pricing data available. Panel B reports annualized Sharpe ratios for weekly rebalanced LMH cross-sectional and timing trading strategies formed using TRS quotes and the basis, restricting the sample to indices and periods for which the TRS data are available.

Panel A: Comparison Between TRS Quotes and Bases

	Start Date	Average Value		Average Magnitude		Correlation
		TRS	Basis	TRS	Basis	
AU	4/29/2016	34	29	37	49	0.48
BD	5/3/2011	22	8	34	32	0.67
CN	4/29/2016	26	-10	32	30	0.33
DJIA	5/3/2011	34	20	35	25	0.77
ES	5/3/2011	38	31	48	64	0.14
EUROSTOXX	5/3/2011	35	21	39	37	0.60
FR	5/3/2011	18	13	24	35	0.39
IT	5/3/2011	33	21	38	44	0.41
JP	5/6/2011	25	9	33	40	0.52
NASDAQ	5/3/2011	39	21	36	26	0.73
UK	5/3/2011	32	18	32	24	0.36
U.S.	5/3/2011	34	13	34	24	0.74
U.S.RU2K	4/29/2016	-9	-17	23	55	0.31
U.S.SPMC	4/29/2016	37	30	37	34	0.48
Average		28	15	35	37	0.49

Panel B: Trading Strategy Annualized Sharpe Ratios

	Cross-Sectional Strategies		Time-Series Strategies	
	Futures	Spot	Futures	Spot
TRS	0.91	0.86	0.54	0.50
Basis	1.08	1.02	0.49	0.44

Table IX
The Futures-Cash Basis, Securities Lending, and Futures Positions

Panel A reports results from a set of univariate regressions of index security lending fees on the futures-cash basis and TRS quotes. Observations are rolling five-day averages. Panel B reports results from regressions of the five-day rolling average of index security lending fees on dealer futures positions. Observations in both panels are sampled weekly. Standard errors are clustered by index and time. t-statistics are reported in parentheses.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: Lending Fees, the Basis, and TRS Pricing

	y =Basis$_t$				y =TRS$_t$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Fee	-0.50*	-0.38	-0.36**	-0.13	-0.23**	-0.16**	-0.24*	-0.15**
	(-2.07)	(-1.42)	(-2.23)	(-0.84)	(-2.97)	(-2.45)	(-1.78)	(-2.19)
R^2	0.01	0.18	0.08	0.25	0.03	0.31	0.10	0.38
Observations	10066	10064	10066	10064	3814	3814	3814	3814
Time FE	No	Yes	No	Yes	No	Yes	No	Yes
Entity FE	No	No	Yes	Yes	No	No	Yes	Yes

Panel B: Lending Fees and Dealer Positions

	(1)	(2)	(3)	(4)
Fee	2.50**	2.89**	0.38*	0.30
	(3.78)	(4.02)	(2.71)	(0.41)
R^2	0.22	0.55	0.37	0.67
Observations	2716	2716	2716	2716
Time FE	No	Yes	No	Yes
Entity FE	No	No	Yes	Yes

Table X
The Futures-Cash Basis, Dealer Positions, and Other Pricing Deviations

The table reports regressions of the futures cash basis on weekly observations of dealers futures positions for the U.S. indices in our sample, interacted with an equity arbitrage index (EQ Arb) and a fixed income arbitrage index (FI Arb). The equity arbitrage index is constructed by taking the absolute value of the futures-cash basis for each non-U.S. index in our sample at each point in time and standardizing the resulting series to have zero mean and unit standard deviation. The fixed income arbitrage index is constructed using the average magnitude of three-month deviations from covered interest rate parity for G10 currencies versus the U.S. dollar, and the *Noise* measure of Hu, Pan, and Wang (2013), which captures the pricing deviation of one- to 10-year bonds from a fitted yield curve. The index is constructed by taking the average of the two series (standardized to have zero mean and unit standard deviation) at each point in time, with the resulting index restandardized to have unit mean and standard deviation. t-statistics are reported in parentheses.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	C_t = Equity Arb. Index				C_t = FI Arb. Index				C_t = Equity Arb. + FI Arb. Index			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dealer	-28.96**	-22.00**	-25.83**	-10.20**	-28.14**	-20.74**	-25.56**	-9.87**	-28.39**	-20.88**	-25.78**	-10.05**
	(-3.71)	(-4.27)	(-3.28)	(-3.19)	(-3.89)	(-4.57)	(-3.28)	(-2.99)	(-3.82)	(-4.43)	(-3.29)	(-3.23)
Dealer× EQ Arb	-8.96***	-8.90***	-7.17**	-7.13**					-6.05**	-6.37**	-4.99*	-5.30**
	(-4.76)	(-5.37)	(-3.10)	(-3.23)					(-3.58)	(-4.10)	(-2.64)	(-3.09)
Dealer× FI Arb					-10.83**	-9.21**	-9.36**	-8.44**	-8.84**	-7.09**	-7.61**	-6.58**
					(-3.89)	(-3.50)	(-3.76)	(-3.37)	(-3.90)	(-3.48)	(-3.61)	(-3.34)
EQ Arb	-2.62	-3.09							-0.93	-1.12		
	(-0.90)	(-1.12)							(-0.35)	(-0.45)		
FI Arb					-3.49	-5.22			-2.81	-4.48		
					(-0.93)	(-1.52)			(-0.81)	(-1.45)		
R^2	0.29	0.35	0.63	0.71	0.31	0.36	0.63	0.71	0.32	0.37	0.64	0.71
Observations	2874	2874	2874	2874	2874	2874	2874	2874	2874	2874	2874	2874
Time FE	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
Entity FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes