NBER WORKING PAPER SERIES

BEYOND BASIS BASICS:
LIQUIDITY DEMAND AND DEVIATIONS FROM THE LAW OF ONE PRICE

Todd M. Hazelkorn
Tobias J. Moskowitz
Kaushik Vasudevan

Working Paper 26773
http://www.nber.org/papers/w26773

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
February 2020, August 2020

We thank Jules van Binsbergen, Thomas Bonczek,Will Diamond, Darrell Duffie, Gary Gorton, Ronen Israel, Michael Katz, Toomas Laarits, Kristoffer Laursen, Ari Levine, Paul Leyzerovich, Lasse Pedersen, Christopher Polk (discussant), Ashwin Thapar, Tuomo Vuolteenaho, Chen Wang, Franklin Wang and seminar participants at AQR Capital Management, Yale SOM, and the 2019 American Finance Association Conference meetings in Atlanta for helpful comments and suggestions. A previous version of this paper was circulated with the title "Beyond Basis Basics: Leverage Demand and Deviations from the Law of One Price." AQR Capital is a global asset manager who may or may not use the insights and methods in this paper. The views expressed here are those of the authors and not necessarily those of AQR, nor of the National Bureau of Economic Research.

Beyond Basis Basics: Liquidity Demand and Deviations from the Law of One Price
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NBER Working Paper No. 26773
February 2020, August 2020
JEL No. F3,F31,F65,G1,G13,G15,G2,G23

ABSTRACT

We argue that deviations from the law of one price between futures and spot prices, known as bases, capture important information about liquidity demand for equity market exposure in global equity index futures markets. We show that bases (1) co-move with dealer and investor futures positions,(2) are contemporaneously positively correlated with spot and futures markets with the same sign, and (3) negatively predict futures and spot market returns with the same sign. These findings are uniquely consistent with our liquidity demand model and distinct from other explanations for bases, such as arbitrage opportunities or intermediary balance sheet costs. We show persistent supply-demand imbalances for equity index exposure reflected in bases, where compensation for meeting liquidity demand for that exposure is large (5-6% annual premium).

Todd M. Hazelkorn
AQR Capital Management
1 Greenwich Plaza
Greenwich, CT 06830
todd.hazelkorn@aqr.com

Tobias J. Moskowitz
Yale School of Management
165 Whitney Avenue
P.O. Box 208200
New Haven, CT 06520-8200
and NBER
tobias.moskowitz@yale.edu

Kaushik Vasudevan
Yale University
kaushik.vasudevan@yale.edu

Introduction

We study deviations from the textbook law of one price in equity index futures, known as bases. The basis is the futures price minus the synthetic fair-value futures price implied by the spot price and the benchmark borrowing rate.[1] The conventional interpretation is that bases reflect differences between benchmark borrowing rates and actual interest rates arbitrageurs can finance their positions in the spot market. In equilibrium, bases emerge from a combination of supply-side frictions that intermediaries face, such as balance sheet costs, as well as the amount of futures demand to be intermediated.[2] If demand for futures exceeds the supply intermediaries are able to provide at current rates, then intermediaries raise the borrowing rates embedded in futures contracts. We refer to these potential demand-supply imbalances as "demand effects," (assuming shocks come from the demand side and identifying these shocks in the data). Intermediary financing costs increase with the amount of futures demand, where long (short) futures demand implies a more positive (negative) basis. Rather than focusing solely on the cost of financial intermediation implied by the basis, we focus on the demand that gives rise to the basis, identifying several new implications that find support in the data.

Focusing on the demand side allows us to explain *cross-sectional* variation in the magnitude of bases across equity indices. Such heterogeneity, which is substantial in the data, is difficult to explain by balance sheet costs alone and has not been explored in previous work. While the link between bases and futures demand is implicitly assumed in work on intermediary financing costs, it has not been directly studied.

In addition to reflecting dealer financing costs, we argue that futures-spot bases in global equity markets reflect liquidity demand for equity index exposure that is common to both futures markets and spot markets. Liquidity demand generates predictions for the relationship between bases and futures and spot prices that are distinct from other explanations for the basis, such as arbitrage forces and balance sheet costs. We present a simple model of liquidity demand in futures markets,

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

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

where liquidity traders and informed traders (whom we refer to as "end users" or "customers") submit orders to futures dealers. Dealers meet futures demand, and perfectly hedge their risk exposure by trading in the spot market with risk-averse liquidity providers, who play the role of market makers. The futures dealers face holding costs that increase with the amount of futures demand they intermediate. These costs are reflected as bases between futures prices and spot prices, with more positive (negative) bases corresponding to long (short) futures demand. The liquidity providers in the spot market take on the equity index exposure offloaded by futures dealers and demand compensation for holding inventory opposite informed demand. Liquidity provider compensation is reflected by an increase in prices contemporaneous with customer demand that eventually reverts after demand abates. Futures prices rise and fall by more than spot prices, corresponding with the additional price impact associated with futures dealer balance sheet costs. The trading behavior of market participants is illustrated in Figure 1.

The model generates three novel predictions for the futures-spot basis. The first is that bases are negatively correlated with the futures positions that dealers hold and positively correlated with the futures positions of customers, since dealers face increasing costs to meet additional futures 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 equity index exposure, which in turn is reflected in increasing futures prices and spot prices. This mechanism generates an additional implication, that changes in dealers' futures positions are contemporaneously *negatively* correlated with futures and spot market returns, while changes in customers' positions are contemporaneously *positively* correlated with futures and spot market returns. The third prediction is that bases negatively *predict* futures returns *and* spot returns (with the same sign). Since bases capture the amount of inventory of liquidity providers in the spot market, more positive inventory corresponds with positive returns in the futures market and the spot market. A corollary is that dealers' futures positions positively predict subsequent futures and spot market returns, and customers' futures positions negatively predict subsequent futures and spot market returns.

We test the first prediction by examining weekly data on dealer inventories and investor positions from the U.S. Commodity Futures Trading Commission (CFTC) for equity index futures. Dealer net positioning is strongly negatively related to the basis, while the net positioning of hedge funds and institutions is positively related to the basis. Cross-sectionally, the basis across equity indices varies positively with the strength of opposing positions between dealers and end-users, which is a novel result consistent with our model. In addition, for a given futures contract, variation in the basis over time corresponds with variation in the size of opposing positions between dealers and end-users. These cross-sectional and time-series results are consistent with futures dealers taking the other side of customer demand for futures, with the total holding costs of dealers (and the size of the basis) increasing with demand. The analysis also uncovers that hedge funds are net demanders, rather than suppliers, of liquidity in equity futures markets. This finding runs counter to hedge fund behavior in other markets, where hedge funds are often liquidity suppliers, and has further implications for the relationship between our results and aggregate funding conditions, which we explore later.

To test the second and third predictions of the model, we examine the relationship of the basis with equity index futures and spot market returns. We find, consistent with the second prediction of the model, that a one percent change in the annualized futures-spot basis corresponds contemporaneously with a 13 to 44 basis point weekly return in futures *and* spot markets (depending upon the fixed effect specification). We also find that a futures-spot basis of one basis point *per week* predicts subsequent futures returns to be 3.9 to 5.1 basis points lower and subsequent spot market returns to be 2.2 to 3.5 basis points lower the following week, consistent with the third prediction of the model. For both predictions, we find evidence that the relationships hold in both time-series comparisons for each index, as well as cross-sectional comparisons across indices. Using the CFTC futures positions, we also test the corollaries to the second and third predictions relating dealer and customer positions to futures and spot market returns, and find consistent evidence with the mechanism captured by the model.

The second and third predictions are unique to our model of liquidity demand explaining the basis in equity index markets. The traditional perspective on bases suggests that these deviations represent an arbitrage opportunity or are solely the result of balance sheet costs. These "convergence-based explanations" only make the prediction that bases should converge to zero when futures contracts expire. They either do not predict a relationship between the basis and spot market returns, or predict that changes in the basis are negatively contemporaneously correlated with spot market returns and positively predict subsequent spot market returns. We find the opposite results in the data. Moreover, convergence-based explanations make an exact prediction that the magnitude of the return predictability of the basis for futures and spot market returns should be less than or equal to the size of the basis. Our results show that futures prices move four to five times *more* than implied by bases simply converging to zero, and spot prices move in entirely the opposite direction. These findings are consistent with our model and inconsistent with traditional views of bases.

The key feature of our explanation is that futures demand, as captured by the basis, also corresponds to liquidity demand for equity index exposure in the underlying spot market. Accordingly, we interpret the return predictability of bases as capturing returns associated with liquidity provision for common equity index exposure. To quantify the magnitude of this compensation, we form two weekly trading strategies. The first is a cross-sectional trading strategy that goes long equity indices with more negative bases and short equity indices with more positive bases. The second is an index timing strategy that takes long positions in equity indices that have positive bases relative to their history and short positions in indices that have negative bases relative to their history. The annualized Sharpe ratio of the cross-sectional strategy is 0.86 when implemented in futures contracts and 0.62 when implemented in spot markets. The Sharpe ratio of the timing strategy is 0.68 when implemented in futures contracts and 0.53 when implemented in spot markets. The returns of these strategies are not explained by exposure to other well known return predictors. The common proxies used to study the returns to liquidity provision in other settings are the returns of five-day reversal strategies (e.g., Jegadeesh (1990), Nagel (2012), and Drechsler et al. (2018)). The returns of the trading strategies we construct are of a similar order of magnitude to the returns of five-day reversal strategies formed with the indices in our sample (Sharpe ratios of 0.78 for the cross-sectional strategy and 0.54 for the timing strategy), but are lowly correlated with five-day reversal strategies and capture a distinct dimension of liquidity provision. Examining the profitability of the trading strategies when using lagged values of the futures-spot basis, we still find return predictability after several weeks and even months, consistent with the high degree of persistence of bases and dealer net positions in futures. Compared with the evidence from individual equities that dealers hold inventories on the order of days (e.g., Hansch et al. (1998) and Hendershott and Menkveld (2014)), our results suggest that the basis is capturing liquidity demand for aggregate equity exposure at a lower frequency.

To better identify the demand-based channel, we use data on flows into exchange-traded funds (ETFs) and open-end funds that are benchmarked to the US indices in our sample. Because these funds primarily purchase shares in the spot market to rebalance their exposure, the flows into the funds capture equity index demand that is reflected in the spot market. We find that flows into ETFs and open-end funds are strongly related to changes in the futures-spot basis, as well as changes in the futures positions of futures dealers and hedge funds. The evidence is consistent with hedge funds using futures and ETFs to rebalance their equity exposure. The results emphasize that the basis captures demand for equity index exposure reflected in both futures and spot market prices, with hedge funds playing an important role.

Analyzing the relationship between funding costs and the futures-spot basis, we document evidence of a mechanism by which equity index futures-spot bases are related to dealer funding costs by examining securities lending. Dealers that sell futures to meet long futures demand hedge their positions by buying stocks in the spot market. They may, in part, finance their stock positions by lending out shares of the stocks that they purchased, as illustrated in Figure 1.[3] When faced with long demand in futures markets, dealers will increase the supply of shares available to borrow in security lending markets, decreasing security lending fees and increasing the financing costs of futures market making. As a result, dealer financing costs increase with long futures demand, as security lending fees decrease. The signs are reversed when dealers face substantial demand for shorting futures. We provide evidence consistent with this mechanism, using data on securities lending fees and quantities for global equities.

Analyzing the relationship between our results and *aggregate* funding conditions, we first document that the magnitude of bases increases when aggregate conditions deteriorate, as proxied by the intermediary capital risk factor of He et al. (2017) and by shocks to the Treasury Minus Eurodollar (TED) spread and the VIX. This evidence is consistent with the size of bases reflecting aggregate funding conditions that impact the cost of futures intermediation. Second, we study the exposure of the trading strategies we construct to funding liquidity and volatility shocks. Funding liquidity and volatility shocks may reflect risk-bearing capacity of leveraged investors (Brunnermeier and Pedersen (2008) and Adrian and Shin (2010)), and hence may be related to the returns of liquidity provision. We find that funding liquidity shocks and volatility shocks are only weakly related to our liquidity trading strategy returns. This result, which is weaker than in other settings, is partly explained by the fact that some of the futures demand captured by bases comes from hedge funds, in contrast to hedge funds playing the role of liquidity providers. We present evidence that hedge funds reduce their equity index exposure in futures when funding conditions deteriorate. Our results suggest that while futures supply might be impaired by shocks to funding conditions, these effects are offset by the corresponding impact on futures demand.

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

Our results offer further evidence for the role that financing costs play in determining asset prices, particularly violations of the law of one price, and their important interaction with asset demand. We connect the literature on intermediation costs to the literature on end-user demand, dealer inventories, and asset prices (De Roon et al. (2000); Chordia et al. (2002); Bollen and Whaley (2004); Garleanu et al. (2009); Hendershott and Menkveld (2014); Greenwood and Vayanos (2014); Boons and Prado (2019), and He et al. (2019)), making clear that financing rates and asset demand are intertwined. 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 et al. (2020)).[4] While other studies primarily focus on the effects of institutional demand on asset prices in individual stocks or specialized assets, we show that institutional demand forces can drive variation in the prices of entire equity markets, related to recent evidence presented by Koijen and Gabaix (2020).

Additionally, our paper is related to work, more broadly, on the role of financial intermediation in asset pricing. The existence of bases in equity index futures markets reflects the fact that the cost of capital for intermediaries in these markets is different from simple uncollateralized borrowing rates (Garleanu and Pedersen (2011)), due to both financial frictions and demand. Our finding that the return predictability of bases reflects compensation for liquidity provision by intermediaries in equity index markets provides another piece of evidence on the role of intermediation in determining asset prices (He and Krishnamurthy (2013); Brunnermeier and Sannikov (2014); Adrian et al. (2014) and He et al. (2017)). We also highlight that heterogeneity among intermediaries is important, echoing results in other work (He et al. (2010) and He et al. (2017)).

The rest of the paper is organized as follows. Section 1 presents a simple model of liquidity demand in futures markets and outlines testable predictions. Section 2 presents the data and methodology for calculating the futures-spot basis in equity index markets. Section 3 tests predictions from the model relating the basis, dealer inventory positions, and returns. Section 4 studies trading strategies in order to quantify the returns to liquidity provision captured by the basis. Section 5 studies the direct relationship of intermediary financing costs with bases via securities lending. Section 6 examines how liquidity supply and demand influence the results. Section 7 concludes.

[4] In a similar spirit to our results, 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.

1 Model of Liquidity Demand for Futures

We present a stylized model of liquidity demand for futures that generates some novel testable predictions. The model 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).

The model illustrates how a basis emerges between futures prices and spot prices due to holding costs that futures dealers face to meet customer demand. In the model, futures dealers perfectly hedge their risk exposure from meeting futures demand by trading in the spot market, where risk-averse liquidity providers demand compensation for holding inventory. The mechanics of this trading are depicted in Figure 1. The model motivates a set of empirical predictions that suggest that futures and spot returns contemporaneously increase with the basis, and are negatively predicted by the basis. These predictions are unique to an explanation based on liquidity demand and distinct from predictions of standard explanations for the futures-spot basis.

1.1 Model Setup

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

The value of the risky asset in the final period T is

$$v_T = v_0 + \sum_{t=1}^{T} \delta_t + \sum_{t=1}^{T} \xi_t, \tag{1}$$

which is paid as a terminal dividend. The innovations δ_t, ξ_t are jointly normal, iid over time, mutually uncorrelated, and have variances σ_δ^2 and σ_ξ^2, respectively.

A futures contract traded in period t is a promise to deliver one unit of the risky asset at the beginning of period $t + 1$. Promises are always fulfilled. Informed traders and liquidity traders cannot trade the risky asset directly, but trade by submitting market orders for the futures contract each period. Liquidity traders trade a random, exogenous amount z_t in period t. z_t is normal, iid over time, uncorrelated with δ_t and ξ_t, and has variance σ_z^2. Liquidity providers cannot transact in futures contracts but serve as market makers for the risky asset.

Futures dealers transact in both the risky asset and in futures. In each period, they serve as market makers for the futures contract and fulfill orders from informed traders and liquidity traders for futures. For each order they receive for a futures contract at time t, futures dealers submit an offsetting opposite order to the liquidity provider for the risky asset. At the beginning of $t+1$, the dealers fulfill the terms of the futures contracts by delivering the risky assets they purchased in period t to the end-users. Futures dealers are perfectly competitive and price futures contracts such that they make zero profit in equilibrium.

The representative futures dealer faces a holding cost that scales quadratically with the the number of risky assets held by dealers in aggregate, i.e.

$$c_t = cx_t^2, \tag{2}$$

where $c > 0$ is a constant, c_t is the total cost faced by dealers and x_t is the total number of risky assets held by dealers in period t. This cost structure can be thought of as a reduced-form catch-all for the costs dealers face to accommodate customer demand for futures over and above the benchmark borrowing cost (e.g., balance sheet costs and related holding costs). The cost dealers face is entirely passed onto futures prices. Because the total cost is quadratic in the total demand, the holding cost is reflected in futures *prices* as linear in the amount of total demand.

The signal ξ_t is public and observed at time t by all market participants. δ_t becomes public information at time t, but informed traders receive a private signal in the previous period, $s_{t-1} = \delta_t$, that provides them a short-lived informational advantage. Informed traders are competitive, myopic, and have CARA utility. The demand function for the representative informed trader is linear in the signal:

$$y_t = \beta s_t. \tag{3}$$

As in Nagel (2012), β is increasing in the aggregate risk-bearing capacity of informed traders and decreasing in the level of risk they perceive and the price impact they expect to have in aggregate on the risky asset price. Additionally, β is also decreasing in c, as informed traders internalize the additional impact their demand has on futures prices via dealer balance sheet costs. (See Internet Appendix A.1 for details.)

The futures dealers meet the demand for $x_t = z_t + y_t$ futures contracts, and submit a market order for x_t units of the risky asset that the liquidity provider satisfies. The representative competitive liquidity provider is also myopic with CARA utility. Her asset demand is given by

$$m_t = \gamma \left(E[\delta_{t+1} | \mathcal{M}_t] + v_t - P_t^s \right), \tag{4}$$

where P_t^s is the price of the risky asset at time t, and $\mathcal{M}_t$ is her information set at time t. γ captures the aggressiveness with which liquidity providers supply liquidity in a reduced form, decreasing in the amount of risk and increasing in the risk-bearing capacity of the market-makers.[5] Because z_t and δ_{t+1} are independently normal, the liquidity providers' expectation of δ_{t+1} is given by

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

where ϕ is defined to satisfy the equation and captures the informativeness of demand, x_t, about the forecastable component of period $t+1$, δ_{t+1}. Imposing market clearing ($x_t + m_t = 0$) provides expressions for the equilibrium prices of the risky asset and the futures contract.

$$P_t^s = \left(\frac{1}{\gamma} + \phi \right) x_t + v_t \tag{Spot Price}$$

$$P_t^f = P_t^s + c x_t \tag{Futures Price}$$

The basis at time t is defined as the difference between the futures price and the spot price.

$$B_t \equiv P_t^f - P_t^s = c x_t \tag{6}$$

The equilibrium dollar return for the risky asset and the period t futures contract are defined as:

$$R_{t+1}^s \equiv P_{t+1}^s - P_t^s = \xi_{t+1} + \eta_{t+1} + \left(\frac{1}{\gamma} + \phi \right) x_{t+1} - \frac{1}{\gamma} x_t \tag{Spot Returns}$$

$$R_{t+1}^f \equiv P_{t+1}^s - P_t^f = R_{t+1}^s - c x_t \tag{Futures Contract Returns}$$

[5] For example, γ can vary because of actual risk-aversion (e.g., as assumed in Grossman and Miller (1988) and Garleanu et al. (2009)) or because constraints induce liquidity providers to behave as if they are risk-averse (e.g., Value-at-Risk constraints, as in Adrian and Shin (2010), or funding constraints, as in Brunnermeier and Pedersen (2008)).

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

The basis scales linearly with the number of futures contracts demanded, as it reflects the balance sheet costs that dealers face 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_{t+1} and z_{t+1} are iid, x_{t+1} is not predictable at time t. For the spot returns, $-x_t$ represents the expected component of period $t + 1$ order flow, and $-\frac{1}{\gamma}x_t$ is the predictable component of returns that compensates the liquidity provider for bearing inventory risk. Futures returns are equal to spot returns plus an additional predictable piece, $-cx_t$, which comes from the balance sheet costs borne by the futures dealers, and represents futures prices converging to the spot price at delivery.

1.2 Model Predictions

We outline three predictions from the model that are distinct from the predictions made by standard explanations for the futures-spot basis (such as the basis being only an arbitrage opportunity or that only balance sheet costs determine the basis).

Prediction 1: The (signed) futures-spot basis has a positive relationship with long futures demand from customers and a negative relationship with dealers' futures positions.
This prediction follows immediately from the definition of the basis from the model ($B_t = cx_t$, where x_t is customer demand for futures). In the model, if customer demand x_t is negative, then the basis will be negative; if customer demand x_t is positive, then the basis will be positive. The basis increases in magnitude with the amount of futures demand.

Recent work has emphasized the role that balance sheet costs play in the magnitude of bases (e.g., Du et al. (2018) and Andersen et al. (2019)). The model emphasizes how the *signed* basis behaves, which balance sheet cost explanations do not emphasize. This prediction is not unique to our model, however. The traditional perspective that the basis represents an arbitrage opportunity would similarly predict that futures prices are increasing in long futures demand from customers. However, the prediction is important to illustrate our mechanism.

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.

In the model, the correlation between changes in the basis and returns comes from the relationship of each with futures order flow, $\Delta x_{t+1} \equiv x_{t+1} - x_t$. Changes in the basis are directly proportional to futures order flow. Spot returns and futures returns are also increasing contemporaneously with order flow, as increasing order flow drives the liquidity providers to demand a higher price. The contemporaneous correlations should be slightly stronger in futures, as the balance sheet costs from futures demand are reflected in futures prices but not spot prices. The corollary follows because futures order flow is directly captured by changes in dealers' and customers' futures positions.

This prediction is unique from other explanations. Traditional explanations that the basis represents an arbitrage opportunity or explanations that focus solely on dealer balance sheet costs do not make this prediction. They might predict that the basis is contemporaneously increasing with futures contract returns, but they would either predict that the basis should be contemporaneously *negatively* related to spot market prices, or that it should be 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 customer futures positions negatively predict subsequent futures returns and spot returns.

This prediction directly follows from the equations for returns. Period $t + 1$ returns are negatively related to the total futures demand in period t, x_t, reflecting compensation to the liquidity provider. The predictive relationship should be stronger for futures, because futures returns include an additional basis term. The corollary follows because dealers and customer positions capture x_t.

This prediction is also unique to our model. Arbitrage or balance sheet cost explanations might suggest that the basis negatively predicts futures returns, but they would either predict no relationship between the basis and subsequent spot returns or they would predict that the basis should be *positively* related to subsequent returns.

1.3 Model Discussion

In the model, the basis between futures and spot prices emerges because of the balance sheet cost that futures dealers face to meet customer demand for futures and hedge their exposure in the spot market. This is consistent with explanations for the basis that have emerged recently (Du et al. (2018), Andersen et al. (2019)).

The predictions of the model are primarily based on the standard insight in market microstructure models that liquidity providers ("market makers" in the standard parlance) earn compensation for carrying inventory in order to meet the demands of investors (Grossman and Miller (1988)). However, the unique predictions relating the basis to prices and returns come from the assumption that customers only trade in futures contracts, which *indirectly* provides them with their desired exposure to the risky asset, and that futures dealers taking the other side of end-user demand hedge their inventory by trading in the spot market. To trade in futures, end-users pay a cost ("the basis"), on top of the price of the risky asset, in order to compensate the futures dealers for the balance sheet costs the dealers face.[6] A natural set of questions arise. How realistic is the mechanism of end-users trading in the futures markets instead of in spot markets? How realistic is it that futures dealers hedge all of their futures inventory? And *why* do investors trade in futures markets, rather than trade directly in the spot market, if there is an additional cost associated with trading futures?

The response to the first two questions is that, of course, in reality, all end-users don't trade in futures rather than spot markets and dealers don't necessarily hedge all of their futures inventory. We expect the model to deliver the same qualitative predictions about the relationship between the basis and futures and spot market returns across different extensions of the model (e.g. extending the model to include a subset of customers trading directly in the spot market, or partial hedging by futures dealers) as long as demand for futures and demand faced by liquidity providers in the spot market are highly correlated and liquidity providers in the spot market are unable to distinguish between informed and uninformed demand. This is an important point for interpreting the model predictions and our empirical results. While in the model, all liquidity demand comes via futures, in reality, liquidity demand for equity market exposure likely occurs in both spot markets and in the futures markets. Our empirical results relating the basis with market returns likely reflect *common* liquidity demand in futures and spot markets, which is further emphasized by our later

[6] We assume that futures dealers are competitive and that the cost embedded in the basis simply represents the balance sheet cost that dealers face. However, it might be the case that in reality, dealers are not competitive. The basis (and the implicit cost) may also partially reflect imperfect competition. See Wallen (2019).

empirical results relating the basis with flows into ETFs. However, our explanation does require that a substantial amount of liquidity demand occurs in futures markets, and that this demand is transmitted to spot markets by futures dealers hedging their exposure.

In response to the third question, there are many reasons that investors trade futures rather than trading stocks directly. Futures are more capital efficient than trading stocks – investors can gain substantial equity market exposure by posting a small amount of margin and holding futures. Gaining a similar amount of long or short equity market exposure on margin by trading cash stocks is more expensive, especially at large sizes. Futures contracts are also standardized and centrally cleared, meaning that market participants can acquire leveraged exposure to an index without taking on potential counterparty risk. Additionally, to replicate an equity index, like, the S&P 500, an investor has to purchase each stock in the index, whereas they only have to execute one transaction to buy S&P 500 futures. Investors that are not informed about cross-sectional differences in single stock returns may also prefer trading in a single "basket" security than in each of the stocks to avoid potential trading costs from adverse selection (Subrahmanyam (1991) and Gorton and Pennacchi (1993)).

One nuance the model is silent on is the frequency over which liquidity demand and liquidity provision occur (i.e., what the frequency of t is). In our empirical analysis, we find evidence that liquidity demand in aggregate equity markets may play out over several weeks, which is a lower frequency than the evidence from individual stocks, where a period may correspond with a few days.

Finally, because the model is effectively a two period model, it does not fully capture some dynamics that may be important in reality. For example, it is worth noting that the balance sheet cost that futures dealers face in the model, c, likely varies over time, and may be correlated with the demand-absorbing capacity of liquidity providers, γ. Others have demonstrated that funding constraints can give rise to bases (Garleanu and Pedersen (2011)) as well as impair the ability of liquidity providers to absorb demand (Gromb and Vayanos (2002) and Brunnermeier and Pedersen (2008)). Accordingly, the magnitude of the futures-spot bases we measure, and the returns to liquidity provision, can be correlated over time through a funding channel, and common shocks to c and γ can affect patterns in prices and returns. Reality also has an added wrinkle that the risk-bearing capacity of informed traders, β in the model, also likely varies over time with aggregate funding conditions. This is especially true if futures demand comes from hedge funds, which we find to be the case empirically. We discuss these potential additions in more depth after analyzing the main predictions of the model.

2 Data and Methodology

We describe the data and methodology for computing bases and present summary statistics.

2.1 Data

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

2.1.1 Computing the Basis

We construct the basis for each index in our sample using the no-arbitrage relation between futures and spot prices,

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

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

Data on risk-neutral dividend expectations are not systematically available for the indices in our sample. From January 2007 through the end of our sample, we use point-in-time forecasts of index dividends provided by Goldman Sachs as our measure of dividend expectations. From 2000 through 2006, we use the realized dividends of an index from t to $t+1$ to proxy for dividend expectations. We conduct a number of analyses to understand the impact of our use of dividend expectations under the physical measure and realized dividends to proxy for dividend expectations under the risk-neutral measure in Internet Appendix A.3, such as analyzing dividend futures in the S&P500, imputing dividend risk premia, and analyzing the timing of dividend announcements. We find that while our treatment of dividends likely introduces small measurement error, this error does not meaningfully affect our headline results.

For the benchmark borrowing rate, we use the local interbank offer rate for each market, constructed by interpolating listed rates to match the maturity of the futures contract. The no-arbitrage relationship between futures and spot prices assumes that dealers are able to finance their market-making activities at the local interbank lending rate, an assumption that is often not true in practice and gives rise to the bases we measure. Accordingly, the bases we measure may or may not capture true "arbitrage" opportunities. Our particular focus here is not on whether bases capture arbitrage opportunities, but rather to focus upon the information about supply-demand imbalances contained in futures prices. The choice of benchmark funding rate (e.g. using local overnight index swap rates rather than interbank rates) impacts the magnitude of bases we measure. Nevertheless, as we show in Internet Appendix A.5, our headline results persist even when looking at cross-sections of indices where the benchmark interest rate is the same.

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

$$\text{Basis}_t = \frac{F_t - \hat{F}_t}{S_t \times TTM} = r_t^{f*} - r_t^f. \tag{8}$$

We normalize by time-to-maturity for comparability across indices with different expiration dates and to capture the decay of the basis as the contract approaches expiration.[7] Equation (8) can be interpreted as the annualized difference between the expected return to holding futures on an index and the expected return to holding the stocks of an index in excess of the local interbank lending rate. It can also be interpreted as the difference between the annualized interest rate implied in the price of a futures contract, r_t^{f*}, and the annualized benchmark interest rate, r_t^f. Given this interpretation, the results also have implications for other work that considers the interest rates embedded in derivatives prices (e.g. Binsbergen et al. (2019)), which we discuss in more detail in Internet Appendix A.7.

To construct the basis, we use pricing data from Thompson Reuters Tick History (TRTH). For

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

spot index prices, the database contains the last traded prices of each index, aggregated from the last traded prices of the individual constituents in the index, provided at a minut frequency. For futures prices, the database contains tick-level data. We compute minute-by-minute futures prices by taking the mid point from the last bid and ask quotes. We calculate a daily value of the basis as the average of the minute-by-minute observations, which reduces estimation error and controls for asynchronous closing prices in futures markets and cash equity markets.[8]

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

2.2 Summary Statistics of the Basis

Table 1 reports summary statistics for the futures-spot basis in global equity markets. We report summary statistics for the full sample, as well as for two sub-samples: January 2000 to June 2007, and July 2007 to December 2017. The average bases, average absolute value of bases, and average time-series and cross-sectional standard deviations of bases are reported (in annualized basis points).[9] For global equities, the average basis is -1 basis point (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, while bases are close to zero on average in global equity markets, there is substantial variation in the basis over time and

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

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

across indices. The magnitude and variation of bases is slightly lower in the post-2007 period than in the pre-2007 period.

Compared with other settings (e.g., currencies), bases are an order of magnitude larger in global equity index markets. For example, after the financial crisis, deviations from covered interest rate parity have been shown to be "large," the bases we measure are more than twice as large. One reason for these differences is due to frictions associated with financing positions. Currency markets are primarily money markets, where the main friction driving the basis appears to be bank balance sheet costs. In global equity markets, there are additional frictions that increase the cost of dealers meeting futures demand, such as securities lending, which we explore in more depth later in the paper.

3 Testing the Model Predictions

We test the three predictions from the model. We test the first prediction by analyzing the relationship between the basis and investor positions in futures contracts for US indices (which are the indices in our sample for which we have futures position data). We test the second and third predictions of the model regarding the relationship between the basis and returns using all of the indices in our sample. We use the investor positioning data in the US to test the corollaries to the second and third predictions.

3.1 Prediction 1: The Relationship Between Futures Positions and the Basis

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

To test this prediction, we use data on futures positions from the CFTC. For financial futures traded on US exchanges, the CFTC publishes the Traders in Financial Futures (TFF) report every Thursday, providing the aggregate long and short positions of investors categorized into four groups: Dealers/Intermediaries, Institutional, Levered Funds, and Other Reportables.[10] For equity

[10]The report officially designates the category "Leveraged Funds", but we will use the term "Hedge Funds" interchangeably to refer to this category. These designations come from Form 40 filings completed by reportable traders, as mandated by the CFTC. The CFTC expounds on these designations, describing Dealers/Intermediaries as participants that "tend to have matched books or offset their risk across markets and clients... These include large banks (U.S.

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

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

This signed measure captures whether investors in a given category are net long or short in aggregate, and scales their net positioning by the open interest.[11]

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

Before directly testing the first prediction, we document some basic facts in the data to provide additional color for our story. Figure 2 plots the time-series of each of the positioning series for each equity index. With the exception of the Russell 2000, Dealer/Intermediary positioning is on average net negative over the sample period, while Institutional and Hedge Fund positioning is net positive (the opposite holds for the Russell 2000 in the sample). For each index, dealers hold the largest net positions, which are negatively correlated with those of all other investor categories.

Table 2 reports the correlations of net positioning across investor categories. Panel A reports the average correlation of net positioning by investor type *within* each index. For example, the entry in the Dealer Column and Institutional row represents the correlation of net positioning of Dealers and Institutional Investors calculated for each index and then averaged across the indices. The average within-index correlation of Dealer and Institutional Investor net positioning is -0.66. Similarly, the average correlation of Dealer and Hedge Fund net positioning is -0.68, and the average correlation of Dealer and Other Investor net positioning is -0.28. The strong negative relationship between dealer positioning and positioning of other types of investors is consistent with dealers taking the other side of futures demand of end-users in equity markets.[12]

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and non-U.S.) and dealers in securities, swaps, and other derivatives." The Institutional Asset Manager designation includes "pension funds, endowments, insurance companies, mutual funds, and portfolio/investment managers whose clients are predominantly institutional," while Hedge Funds are described as including "hedge funds and various types of money managers, including registered commodity trading advisors (CTAs); registered commodity pool operators (CPOs) or unregistered funds identified by the CFTC." The "Other" category includes traders who "mostly are using markets to hedge business risk, whether that risk is related to foreign exchange, equities, or interest rates."

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

[12] The negative correlations need not imply that dealers are expanding their balance sheets to provide futures expo-

Panel B of Table 2 reports the average pairwise correlation of net positioning by investor type *across* indices. For example, the entry in the Dealer row and Dealer column corresponds to the average pairwise correlation of net positioning of Dealers in one index with Dealer positions in the other indices, averaged across all indices. Dealer positioning is, on average, 0.37 correlated across indices. For other investors, positioning is likewise positively correlated across indices, with the strongest correlation for Hedge Funds (0.39). Taken together, the results from Panels A and B of Table 2 indicate that dealer and end-user positions are strongly negatively correlated for a given index, and that positions by investor type are positively correlated across equity indices.

We test the relationship between dealer positions and the basis by running a panel regression of annualized futures-spot bases on dealer net positioning. Table 3 reports that there is a strong negative relationship between dealer net positioning and the basis. The coefficient on dealer positioning (which is scaled to mean zero and unit variance) is strongly significant, with a t-statistic of -3.74 (column (1)). Adding entity, time, and entity and time fixed effects reduces the coefficient, but still yields a strong and significant negative relationship. The negative relationship holds in both the time-series and the cross-section. For a given futures contract, the basis declines as dealer net positioning increases, and across indices the basis is smaller when dealer net positions are larger. The results suggest that a one standard deviation increase in dealer positioning corresponds to a 28.9 basis point decrease in the basis. Including time and entity fixed effects, the effect is a 10 basis point drop. In times and for indices where dealers have substantial long (short) positions, the basis is more (less) negative. These findings are consistent with dealer balance sheet costs playing a role in the basis. The size of dealers' position in futures increases the cost they face to provide additional futures exposure, resulting in a bigger wedge between futures and spot prices.

We next investigate the relationship between end-user positioning and the futures-spot basis. We run multivariate regressions of the futures-spot basis on net positioning by Institutional investors, Hedge funds, and Other investors. The last four columns of Table 3 report the results. Across all specifications, Institutional investor positioning is significantly positively related to the futures-spot basis. A one standard deviation change in institutional investor positioning leads to a 6.7 to 20.6 basis point increase in the futures-spot basis, depending on the fixed effects specification. Hedge fund positioning is also positively related to bases, with a one standard deviation

sure to end-users. If end-users demand to purchase assets held by dealers, then dealers may reduce their balance sheets while meeting end-user demand. However, combined with the evidence of the persistent opposing signs of dealer and end-user positioning, the results suggest that dealers are taking on futures inventory to meet end-user demand, and the amount of inventory they take depends upon the amount of futures exposure demanded by end-users.

change in hedge fund positioning corresponding to a 3.8 to 19.7 basis point increase in the futures-spot basis. Other investor positions are also related to the basis, though the coefficients are smaller.

In Internet Appendix Figure A.3, we report the t-statistics from time series regressions of the basis on the net futures positioning of each investor category for each individual US index. The figure shows that the positive relationship between the basis and dealers futures positioning, and the negative relationship of the basis with hedge fund futures positioning and institutional investor futures positioning holds for *every one* of the five US indices in our sample, providing further evidence in support of our story.

The relationship between hedge fund positioning and the basis is interesting. While hedge funds are known to play the role of liquidity suppliers in some markets, the relationship between hedge fund positioning and the basis suggests that hedge funds are on the demand side in equity index futures markets. The idea that hedge funds are demanders in equity index futures is further emphasized by the strong negative correlation of hedge fund positioning with futures dealer positioning. We return to this point when discussing how aggregate funding conditions, which may affect liquidity providers, futures dealers, *and* hedge funds, relate to our results.

Overall, Table 3 shows that investor positioning captures substantial variation in futures-spot bases, explaining 26% of the variation over time and across markets without any controls and 69% of the variation in combination with time and entity fixed effects. The basis is strongly negatively correlated with dealer positioning in futures, and strongly positively correlated with end-user positioning in futures, consistent with Prediction 1 that the basis varyies with the size and direction of dealers' provision of futures to end-users. In Section 5, we present evidence for a specific mechanism, securities lending fees, by which dealer financing costs are related to the amount of futures demand that dealers intermediate.

3.2 Prediction 2: The Contemporaneous Relationship Between the Basis and Returns

The second prediction from the model 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:

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

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

where $Basis^i_t$ is the futures-spot basis in market i measured in period t, $r^i_{t:t+1}$ 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 are time-fixed effects, and c and γ are the coefficients of interest that measure the contemporaneous relationship between the basis and returns. Regressions are estimated using weekly data, with the basis scaled to be in annualized percentage points (returns are multiplied by 100). Standard errors are clustered by time and entity.

Panel A of Table 4 reports the results. The first four columns display the results for regressions where the dependent variable is the futures returns for a given market. Coefficients range from 0.44 with no fixed effects (t-statistic of 5.25) to 0.17 with time and entity fixed effects (t-statistic of 5.39). The last four columns of Panel A report regression results where the dependent variable is spot returns for a given market. Coefficients range from 0.41 with no fixed effects (t-statistic of 4.99) to 0.13 with time and entity fixed effects (t-statistic of 3.91). The regression coefficients suggest that a 100 basis point move in the annualized futures-spot basis corresponds with a 17 to 44 basis point weekly futures market return, and a 13 to 41 basis point weekly spot market return, which are both large. For context, the average weekly return across all indices from 2000 to 2017 is only 10 basis points.

In Internet Appendix Figure A.4, 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, futures returns, and spot returns is positive for seventeen of the eighteen indices in our sample, providing further evidence that the contemporaneous relationship between changes in the basis and returns is consistent 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 bases and futures and spot market returns is consistent with a unique prediction of our model that bases capture futures demand that is also reflected in the spot market. Other theories of the futures-spot basis that focus on the convergence of the basis, do not predict this observed relationship. They would either predict no relationship between the basis and spot market returns, or they would predict that the relationship should be opposite that with futures returns.

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

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

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

where $F^c_{i,t}$ is the net positioning of investor category c at time t in index i. Changes in investor net positioning are standardized to have zero mean and unit standard deviation (returns are multiplied by 100). Standard errors are clustered by entity and time.

Panel B of Table 4 reports the regression results. We report results for specifications that include both time and entity fixed effects. The first four columns display results for the regressions where the dependent variable is futures market returns and the last four columns display results where the dependent variable is spot market returns. The results suggest that a one-standard deviation increase in futures dealer positioning corresponds with a -15 basis point weekly futures market return (t-statistic of -3.16) and a -14 basis point weekly spot market return (t-statistic of -3.08). Looking to end-user positioning, the regression results suggest that a one-standard deviation change in institutional investor positioning corresponds with a 15 basis point weekly futures return (t-statistic of 7.14) and a 14 basis point weekly spot market return (t-statistic of 6.99). A one-standard deviation change in hedge fund positioning corresponds with a 7 basis point weekly futures return (t-statistic of 1.54) and a 7 basis point weekly spot market return (t-statistic of 1.45). For context, the average weekly return of all US indices over the period for which we have positioning data (2006 to 2017) is about 20 basis points, so the magnitude of the relationship between futures positioning and returns is large.

These results, combined with the evidence for Prediction 1, provide support for the mechanism by which changes in the basis are contemporaneously related to futures and spot market returns. In particular, bases capture 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 with rising futures and spot market prices.

3.3 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 a set of panel regressions,

$$r^{fut}_{i,t+1} = \quad a_i + b_t + cBasis_{i,t} + \epsilon_{i,t+1} \tag{14}$$

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

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

Panel A of Table 5 reports the results from the regressions. The first four columns of the panel report the results for regressions where the dependent variable is futures returns for a given market. Coefficients in the futures market regressions range from -5.1 with no fixed effects (t-statistic of -3.42) to -3.8 with time and entity fixed effects (t-statistic of -4.21). The last four columns of the panel report the results for regressions where the dependent variable is spot returns for a given market. Coefficients in the spot market regressions range from -3.5 with no fixed effects (t-statistic of -2.50) to -2.2 with time and entity fixed effects (t-statistic of -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 negative and significant relationship between the basis and the subsequent week's futures and spot returns is consistent with our liquidity demand-based explanation for the futures-spot 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. Convergence-based explanations of the basis might predict that the basis negatively forecasts subsequent futures returns, but they would predict either zero relationship or a positive predictive relationship between the basis and spot returns – the opposite of what we find in the data.

Moreover, the standard formulations of convergence-based explanations of the basis make exact predictions about the magnitude of the coefficients from the regressions. Alternative explanations that focus just on the convergence of the basis (and do not account for the common liquidity demand in futures and spot markets) suggest that the only predictive relationship between the basis and returns comes from the basis converging to zero. We scaled the variables in the regression so 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. The evidence from the regression in Table 5 clearly rejects these predictions and is inconsistent with convergence-based explanations. Futures prices move four to five times *more* than predicted by futures prices converging to spot prices, and spot prices move in entirely the *opposite* direction. The evidence points to futures prices and spot prices responding to other forces in addition to convergence. We argue this other force is common liquidity demand reflected in the basis.

In Internet Appendix Figure A.5, we also report the 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 fourteen of the eighteen 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, that dealer futures positions should positively predict subsequent futures and spot returns, and that customer futures positions should negatively predict subsequent futures and spot returns. Using the CFTC investor net positioning data, we run the following panel regressions,

$$r_{i,t+1}^{fut} = a_i + b_t + gF_{i,t}^c + \epsilon_{i,t+1} \quad (16)$$

$$r_{i,t+1}^{spot} - r_{f,t} = \alpha_i + \beta_t + \gamma F_{i,t}^c + \eta_{i,t+1} \quad (17)$$

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

Panel B of Table 5 reports the results (with time and entity fixed effects). A one standard deviation difference in weekly futures dealer positioning corresponds with a 6.1 basis point higher weekly return in futures markets (t-statistic of 3.52) and a 5.7 basis point higher weekly spot market return (t-statistic of 3.48) in the following week. Since the average weekly futures return for US indices is about 20 bps, these numbers suggest that the relationship between dealer positioning and returns is substantial. A one standard deviation difference in institutional investor positioning corresponds with a -3.6 basis point lower weekly return in futures (t-statistic of -1.72) and a 3.2 basis point lower weekly spot return (t-statistic of -1.58) in the following week. A one standard deviation difference in hedge fund positioning corresponds with a -6.7 basis point lower weekly futures return (t-statistic of -3.45) and a -6.5 basis point lower weekly spot return (t-statistic of -3.30) in the following week.

The regression results provide further evidence for the mechanism driving the return predictability of bases for futures and spot markets. The evidence is broadly consistent with dealers meeting equity index futures demand from customers, and offloading their risk exposure into spot markets. The futures and spot market return predictability reflects compensation to liquidity providers for taking on equity market risk opposite customer demand.[13]

4 Quantifying the Returns to Liquidity Provision

To quantify the magnitude of the returns to liquidity provision in these markets, we construct trading strategies based on the basis. It is well known that liquidity providers demand substantial compensation for meeting liquidity demands in individual equities, as others have studied using data on market maker inventories (e.g. Hendershott and Seasholes (2007) and Hendershott and Menkveld (2014)) and short-term reversal strategies (e.g. Lehmann (1990), Jegadeesh (1990), Nagel (2012) and Drechsler et al. (2018)). However, the returns to liquidity provision for aggregated portfolios, such as equity indices, have been less extensively studied.[14]

4.1 Cross-Sectional LMH Liquidity Demand Strategy

We construct a Low-Minus-High (LMH) Liquidity Demand trading strategy that goes long equity indices where futures are "cheap" relative to spot market prices and short equity indices where

[13] Interestingly, it appears that, at least in the US sample, the net futures positioning of hedge funds negatively predicts subsequent returns, and more than that of institutional investors. Because the position-level regressions include entity fixed effects, the results do not mean that hedge funds necessarily lose money on their futures positions (in fact, hedge funds often trade on time-series momentum in futures, which is highly profitable, see e.g. Moskowitz et al. (2012)). However, the results do support the interpretation that futures demand from hedge funds may lower the subsequent returns of an equity market.

[14] Nagel (2012) is an exception, studying weekly reversal strategies in industry portfolios in addition to reversal strategies in individual stocks.

futures are "expensive" relative to spot market prices. We construct two versions of the strategy: one that trades exclusively in futures and one that trades exclusively in the spot market. These strategies are distinct from the conventional basis trade, which trades futures versus the underlying securities. Rather, we trade cheap futures versus expensive futures in the cross-section, and do the same in the spot market separately. Positive returns to the strategies suggest that markets where futures are trading cheap relative to their "fair values" outperform markets where futures are trading expensive relative to their fair values.

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

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

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

where N_t is the number of available securities at time t, and the scalar κ_t ensures that the sum of the long and short positions equals \$1 and \$$-1$, respectively. X_t^i is the signal used to form the portfolio, and $R_{LD,t}$ is the return at time t of the LMH Liquidity Demand portfolio. This is similar to the weighting scheme employed by Asness et al. (2013), who show that the resulting portfolios are highly correlated with other zero-cost portfolios that use different weights. In the main specification, the signal we use is the one-day lagged basis for index i at time t for X_t^i, and we form portfolios on Friday of each week. In additional tests, we use lagged values of the basis to sort portfolios, and also consider portfolio returns rebalanced on the last business day of each month.[15]

[15] Given that five out of the eighteen equity indices in our sample are US indices, we test the robustness of our results by constructing an alternative global equity LMH Leverage Demand portfolio excluding all US indices except the S&P500, and an additional alternative portfolio excluding all US indices. The resulting portfolios are highly correlated with our baseline specification and realize similar performance. The results are reported in the Internet Appendix A.6.

4.2 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

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

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

4.3 LMH Liquidity Demand Strategy Returns

Table 6 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 monthly rebalancing. For comparison, we also report statistics for cross-sectional and timing reversal strategies. Panel A reports statistics for one-week reversal strategies rebalanced at the end of each week, and Panel B reports statistics for one-month reversal strategies rebalanced at the end of each month.

Panel A reports the annualized Sharpe ratio of the cross-sectional LMH portfolio is 0.86 in futures and 0.62 in the spot market, while the annualized Sharpe ratio of the timing portfolio is 0.68 in futures and 0.53 in the spot market. The performance of the strategies is of a similar order of magnitude to the performance of one-week reversal strategies formed in our cross-section, another proxy for the returns to liquidity provision (Jegadeesh (1990), Nagel (2012), and Drechsler et al. (2018)). We find no evidence of negative skewness for the LMH Liquidity Demand strategies, but some evidence of excess kurtosis.

Panel B shows that the performance of the LMH Liquidity demand strategies persists, even at lower rebalance frequencies. The Sharpe ratio of the monthly rebalanced cross-sectional LMH portfolio is 0.84 when implemented in futures and 0.72 when implemented in the spot market. The monthly-rebalanced timing LMH portfolio has a Sharpe ratio of 0.39 when implemented in futures and 0.32 when implemented in the spot market. These results stand in contrast to the more substantial decay in performance of reversal strategies as we move to the monthly frequency. The cross-sectional reversal strategies have Sharpe ratios of 0.39 (in futures) and 0.32 (in spot). The monthly timing reversal strategies have Sharpe ratios of -0.39 (in futures) and -0.40 (in the spot market), consistent with equity indices exhibiting one month continuation in the time-series, as documented by Moskowitz et al. (2012). The evidence suggests that the LMH Liquidity Demand strategies are picking up a distinct dimension of liquidity demand and supply not captured by short-term past price changes.

The returns of the LMH portfolios are stronger when the portfolio is implemented with futures than when it is implemented in the spot market because the futures strategy also earns profit from the basis converging to zero. However, the returns to the strategy are still substantial when implemented in the spot market. With weekly rebalancing, in the cross-sectional strategy, the annualized average return of the strategy trading in futures is 7.21% per year, while the average annualized return of the strategy trading in the spot market is 5.22%. The difference between the two, 1.99%, captures 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, and are not coming from the convergence of the basis.

4.4 Lagging the Basis

We next study the impact of lagging the basis on the profitability of the LMH Liquidity Demand strategy. We form cross-sectional and timing portfolios following Equations (18) and (20), where the signal is the futures-spot basis lagged n-(week)days, in addition to the one-day implementation lag in the main specification. We consider values of n ranging from 0 to 100 days. Figure 3 plots the Sharpe ratios of the returns of the portfolios. The first plot in the figure displays results for the cross-sectional strategies. Lagging the signal an additional week, the strategy Sharpe ratios are 0.61 and 0.55 when implemented in the futures and the spot market, respectively. The two-week lagged strategies have Sharpe ratios of 0.27 and 0.21. The observed decay from lagging the signal is consistent with the strategy capturing the returns to liquidity provision. The signal becomes stale in its ability to capture information about liquidity provider positions over time as liquidity providers clear their inventory. However, the plot also reveals some evidence that the cross-sectional return predictability of the basis may be more persistent. The results suggest that bases predict cross-sectional returns on the order of weeks to months. The results are also potentially suggestive of seasonal patterns in liquidity demand captured in the basis.

The second plot in Figure 3 plots the Sharpe ratio of the LMH Liquidity Demand timing portfolio against the number of days the signal is lagged. The time-series return predictability of the basis decays more quickly than the cross-sectional return predictability, though it still displays persistence on the order of weeks. Lagging the signal an additional week, the Sharpe ratio is 0.29 and 0.25 in futures and in the spot market. Lagging the signal two weeks, the Sharpe ratios are 0.39 and 0.34. Again, there is evidence that the signal captures lower frequency variation.

One way to further understand the persistence of the return predictability of the basis is to directly analyze the persistence of the basis and the persistence of dealer futures positions. The first plot in Figure 4 displays the daily autocorrelation function plot for the basis, estimated over all indices in our sample. The daily AR(1) coefficient is 0.7, and autocorrelations decay nearly monotonically over time. The autocorrelation of the basis with the one-month lagged basis is about 0.2, consistent with much of its return predictability occurring within a month. Autocorrelations of the basis remain significant for lags of up to 90 weekdays, which is also consistent with the evidence of the longer-horizon return predictability results we observe. We do not observe the quarterly seasonality observed in the cross-sectional strategy returns, though there is an uptick in autocorrelations of the basis at lags of around one year. The second plot in Figure 4 displays the weekly autocorrelation function plot for dealer positions, estimated for US indices. The weekly AR(1) coefficient is 0.96, with autocorrelations decaying monotonically over time. Autocorrelations are still significant using values lagged by one year. The evidence suggests that net dealer positions are even more persistent than captured by the basis.

The persistence of dealer positions, the basis, and its return predictability is notable when compared to the evidence in individual stocks, where liquidity providers only hold inventories on the order of a few days. For example, Hansch et al. (1998) report that the average half-life of dealer inventory positions at the London Stock Exchange is roughly two days. Hendershott and Menkveld (2014) find half-lives ranging from half a day for large stocks to two days for the smallest stocks, using data on market-makers inventories at the New York Stock Exchange. This horizon of liquidity provision in individual stocks is consistent with the horizon of one to five days used to study reversal strategies in Nagel (2012) and Drechsler et al. (2018). The persistence of the basis in equity indices and its return predictability suggest that liquidity supply and demand imbalances may be more persistent at the equity market level than for individual stocks. The persistence of the basis and dealer futures positions are consistent with the interpretation that the basis is capturing a different dimension of liquidity provision than short-term reversals.

4.5 Spanning Tests and Factor Exposures

Table 7 reports regression results of the LMH strategy returns on the other known return factors in equity indices (value and momentum (from Asness et al. (2013), updated from the AQR Data library), time-series momentum from Moskowitz et al. (2012), updated from the AQR Data Library) and carry (from Koijen et al. (2018)). We also include the returns of a weekly rebalanced, passive long strategy holding an equal weight in each of the equity indices in our sample, as well as the returns to one-week reversal strategies, as independent variables in the regressions. Since the returns of other return predictors are available on a monthly frequency, we aggregate the returns of the weekly rebalanced portfolios to a monthly frequency and run the regressions.

The first two columns report results for the LMH strategies implemented in futures. The cross-sectional LMH portfolio in futures loads positively on the momentum portfolio (t-statistic of 2.48), but insignificantly on the other factors. The strategy earns an alpha of 56 basis points per month (t-statistic of 3.44), with an annualized information ratio (alpha divided by residual volatility) of 0.86. In the second column of the table, the timing portfolio in futures has a positive loading on the momentum portfolio (t-statistic of 3.35), the passive long portfolio (t-statistic of 3.61), and the one-week reversal strategy (t-statistic of 2.98). The timing portfolio has a negative loading on time-series momentum (t-statistic of -4.27). The strategy earns an alpha of 118 basis points per month (t-statistic of 3.07), with an annualized information ratio of 0.76.

The third and fourth columns of the table report regression results using the returns of LMH strategies implemented in the spot market. The factor loadings are similar to the strategies trading in futures. The cross-sectional portfolio earns a monthly alpha of 41 basis points per month (t-statistic of 2.49), corresponding with an information ratio of 0.62, and the timing portfolio earns a monthly alpha of 91 basis points per month (t-statistic of 2.39), corresponding with an information ratio of 0.59. The results suggest that the returns of the LMH Liquidity Demand strategies cannot be explained by exposure to other well-known factors in global equity indices. With regards to reversal strategies, the evidence is consistent with LMH Liquidity Demand strategies capturing a different dimension of liquidity provision than reversal strategies. Additionally, the LMH timing strategies are strongly negatively correlated with time-series momentum. This negative exposure is consistent with the results in Moskowitz et al. (2012) that "speculators" (primarily hedge funds and commodity trading advisors) trade time-series momentum in futures contracts. In equity index futures, we show that dealers are primarily on the other side of hedge fund trading. While time-series momentum strategies are highly profitable in the sample, the results suggest that, conditional on the negative exposure to the time-series momentum strategy, trading in the same direction as liquidity providers in equity index markets carries a high alpha. This alpha is consistent with liquidity providers earning compensation for absorbing demand.

5 Futures Dealer Financing Costs, Securities Lending, and the Futures-Spot Basis

To more closely study the mechanism by which dealer financing costs increase with equity index futures demand, we examine the relationship between supply-demand imbalances for equity index exposure, the basis, and securities lending fees.

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

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

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

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

We test the relationship between the basis and security lending measures by running regressions of year-on-year changes in the futures spot-basis on year-on-year changes in each of the security lending measures. We use the Hansen-Hodrick correction to adjust standard errors for overlapping observations.[16] Panel A of Table 8 reports the results. The coefficient on security lending utilization is significantly negative and indicates that a 10% increase in security lending utilization corresponds to a decrease of 19 to 29 bps in the basis, depending on the regression specification. The last four columns of Panel A repeat the regressions using lending fees as the independent variable. The coefficient on security lending fees is significant at the one percent level across all specifications, where a one percent increase in the stock lending fee corresponds to a 29 to 35 basis point decline in the basis.

This evidence suggests an economically significant relationship between the basis and security lending costs. Moreover, the evidence is also consistent with the basis increasing in end-user demand for long-equity exposure that is not offset by corresponding demand for short-equity exposure. There are two potential mechanisms at play, both of which might be happening, that are consistent with our story. The first is that dealers are increasing the supply of shares available to borrow in the cash-equity market when faced with demand for futures, where the increased supply

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

reduces security lending utilization and fees and increases the basis. The second potential mechanism is that there is a negative relationship between the basis and shorting demand in the cash equity market. A primary purpose of the equity security lending market is to facilitate shorting. High demand to short, by borrowing shares in the underlying, reduces financing costs to meet long demand in the futures market for dealers, resulting in a smaller basis. For both mechanisms, the basis is increasing in end-user demand for long-equity exposure that is not offset by corresponding demand for short-equity exposure.

Finally, we examine how index level security lending utilization and fees are related to dealer net positioning in futures, to come back full circle to the results in the previous subsections. Panel B of Table 8 reports results from regressing net futures positioning changes on security lending utilization and fees. There is a positive relationship between dealer positioning and securities lending measures, consistent with the theory. Point estimates range from 3.2 to 8.3, depending upon the fixed effects included, and indicate that a 10 percent change in security lending utilization corresponds to a 0.32 to 0.81 standard deviation change in dealer net positioning. Coefficient estimates on security lending fees are also significantly positive across all specifications, and indicate that a one percent increase in an index's security lending fee corresponds to a 0.46 to 0.63 standard deviation increase in dealer net positioning. This evidence is consistent with the futures-spot basis reflecting the financing cost in excess of benchmark borrowing rates that dealers face to hedge their equity exposure, which is affected both by demand pressure from investors in futures markets and securities lending costs.

6 Liquidity Supply and Liquidity Demand

6.1 Liquidity Demand: Evidence from Fund Flows

To further study the role that liquidity demand plays in giving rise to bases, we examine fund flows to capture liquidity demand in the spot market, which provides tighter identification for our story. Others document the effects that flow-induced price pressures may have on individual stock returns (Coval and Stafford (2007), Lou (2012), and Khan et al. (2012)), so it is possible that flows may capture demand at the market level.

We obtain data on daily net flows and fund sizes for US open-end funds and exchange traded funds (ETFs) from 2007 through 2017 from Morningstar Direct, for all funds for which data is available at a daily frequency. We construct a weekly proxy for flow-based demand for each of the five US 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 respond to inflows largely by purchasing the shares of stocks in the underlying index, so flows broadly correspond with liquidity demand for index exposure.

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 where there are inflows associated with that index. Panel A of Table 9 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 with a 1.9 to 2.7 basis point increase in the weekly basis (which has a standard deviation of 30 basis points). This relationship is consistent with the idea that liquidity demand for index exposure corresponds with a larger basis.

We next run panel regressions of the weekly changes in futures positions on the flow driven demand measure. Panel B of Table 9 reports regression results where the dependent variable is changes in dealer net positioning. As before, we standardize the positioning variables to have zero mean and unit standard deviation, meaning that the coefficients can broadly be interpreted as correlations. Coefficients range from -0.15 (with time and entity fixed effects) to -0.25 (with time fixed effects only), with t-statistics ranging from -3.85 to -4.93. The results suggest a strong negative relationship with dealer positioning and mutual fund flows, suggesting that the demand that dealers face in futures markets is highly correlated with flows into ETFs and open-end funds. Panels C and D report results from panel regressions where the dependent variables are changes in Hedge fund and Institutional investor net positioning. The relationship between weekly flows and changes in the positions of hedge funds is highly significant, with coefficients ranging from 0.15 (t-statistic of 3.94) with time fixed effects to 0.24 (t-statistic of 7.43) with entity fixed effects. None of the regression coefficients on the flow-based measure are statistically significant in the Institutional Investor position regressions, though the coefficients are consistently positive. The evidence suggests that our flow-based demand variable captures demand for futures by 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 occur through two channels, both of which are consistent with liquidity demand. The first channel, which we believe is likely the more dominant one, is that 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 positioning.[17] The second channel is that open-end funds and ETFs facing inflows themselves use futures to rebalance their market exposure. For example, the BlackRock iShares S&P 500 ETF is listed as holding S&P 500 futures contracts.

The results from the relationship between flows, the basis, and investor positions support an interpretation of the futures-spot basis corresponding with liquidity demand that is reflected in the spot market. Funds that need to rebalance their index exposure rebalance their portfolios using futures and ETFs, corresponding with an increase in the basis and a decrease in dealer net positioning. The evidence supports the role that demand for equity index exposure plays in the basis and its return predictability.

6.2 Relationship with Aggregate Funding Conditions

The returns to liquidity provision are an equilibrium result that depends on the capacity of liquidity providers to absorb demand (γ in the model) as well as on the amount of demand that liquidity providers face (x_t in the model). The conditions that affect these quantities may also be related to the balance sheet costs that futures dealers face to intermediate in futures markets (c in the model).

We first analyze how the magnitude of the bases we measure vary with the intermediary capital risk factor of He et al. (2017) (which proxies for innovations to the intermediary sector's marginal value of wealth), innovations to the Treasury minus Eurodollar (TED) spread (as a measure of shocks to the ease or difficulty with which intermediaries may finance positions), and innovations to the VIX (as a measure of volatility risk and shocks to the level of aggregate risk). In the context of the model, this analysis is meant to capture how c, the balance sheet cost of futures dealers, varies with aggregate conditions. Of course, the aggregate variables used may be related to other quantities in the model, so this test is not perfectly identified. However, the tests provide additional verification that shocks to aggregate funding conditions can affect bases, via their impact on dealer balance sheet costs.

[17] Relatedly, Brown et al. (2020) explore mispricings from non-fundamental demand in ETFs.

To measure changes in the magnitude of the basis at a given point in time we compute the average change in the absolute value of the basis for each index, and the change in the cross-sectional standard deviation of the basis across indices. We regress weekly changes in the magnitude of bases on weekly innovations to the liquidity variables, with the independent variables standardized to have zero mean and unit standard deviation, and scaled so that the expected sign in the regression is positive (increases in the independent variables correspond with deteriorating aggregate conditions). We exclude observations for the week of the Lehman Brothers failure. Including this week strengthens the regression relationships we document, because bases and liquidity variables all spike substantially, but the week unduly influences the regression results.

Table 10 reports the results from the regression. All coefficients on the liquidity variables are positive, suggesting that the signs of the relationships are as expected, and most statistically significant. A one standard deviation shock to the liquidity variables increases the magnitude of the basis from 3.2 to 8.6 basis points, depending upon the regression specification. The result is consistent with dealer balance sheet costs varying with aggregate funding costs that is reflected in larger bases. The coefficients from the regressions do not control for the behavior of market participants corresponding with the shocks. If futures dealers reduce their net futures positions corresponding with deteriorating conditions, then the coefficients are a lower bound for the increase in the magnitude of balance sheet costs embedded in the basis.

We next analyze how aggregate funding conditions are related to the LMH Liquidity Demand strategies by regressing the strategies' returns on funding liquidity variables. Our model does not directly speak to this question. The logic behind this analysis is that deteriorating funding conditions may correspond with shocks to the risk-bearing capacity of leveraged investors that face binding funding constraints, which in turn cause these investors to deleverage and reduce their positions. In our setting, if liquidity providers face funding constraints (e.g., Brunnermeier and Pedersen (2008)), then we may expect the LMH strategies to perform poorly coincident with deteriorating funding conditions.[18] However, this effect may be muted by leveraged investors on the demand side (e.g., hedge funds) facing funding constraints as well, and thus reducing their futures demand with funding liquidity shocks (e.g., Brunnermeier et al. (2008)).

We run regressions of the LMH Liquidity Demand returns on variables related to aggregate

[18] Drechsler et al. (2018) present an alternative channel by which volatility shocks may be negatively related to the returns to liquidity provision strategies, showing that liquidity provider positions are directly exposed to volatility shocks in a Kyle (1985) model with stochastic volatility.

conditions, including the lagged monthly level of the VIX. Nagel (2012) shows that the VIX positively predicts the returns of five-day reversal strategies, capturing the increased returns liquidity providers demand when volatility is high. All variables are signed such that positive coefficients correspond with the trading strategies performing poorly coincident with shocks to volatility and funding liquidity.

Panel A of Table 11 reports results from univariate regressions, while Panel B reports results from regressions that include a control for the global market return, which we construct as the returns of a weekly rebalanced, equally weighted basket of the indices in the sample. All returns in the regression are multiplied by 100, and the liquidity variables are standardized so that coefficients can be interpreted as the number of percentage points returns change with a one-standard deviation change in the variable. The timing strategies implemented in futures and in the spot market have significant loadings on the intermediary capital ratio factor, the TED spread, and shocks to the VIX, with the expected signs. The coefficients indicate that one standard deviation shocks to these variables correspond to a change in weekly returns of 44 to 68 basis points, with t-statistics ranging from 4.16 for the TED spread to 6.99 for the intermediary capital ratio. However, after controlling for the market return, in Panel B, only the loading on the TED spread remains significant, with coefficients of 0.31 and 0.28 in futures and spot markets (t-statistics of 2.91 and 2.69). The cross-sectional strategies do not have statistically significant loadings in any of the specifications, with many of the signs going in the opposite direction as predicted.

The results suggest that the LMH Liquidity Demand returns are modestly affected by aggregate funding conditions. Given the wealth of theoretical and empirical evidence that aggregate funding conditions should matter for the returns of liquidity provision strategies, this modest result seems a bit surprising. However, deteriorating funding conditions may also reduce futures demand, which provides a counterbalancing effect. To test this idea, we use investor futures positioning data to examine their behavior with funding liquidity and volatility shocks, taking an approach similar in spirit to Brunnermeier et al. (2008). Using the net positioning data from the Traders in Financial Futures report, we run panel regressions of the form,

$$\Delta F_t^{i,c} = \beta_{VIX} \times \Delta VIX_t \times \text{sign}(F_{t-1}^{i,c}) + \lambda_{VIX} F_{t-1}^{i,c} + \eta_{i,VIX} \quad (21)$$

$$\Delta F_t^{i,c} = \beta_{TED} \Delta TED_t \times \text{sign}(F_{t-1}^{i,c}) + \lambda_{TED} F_{t-1}^{i,c} + \eta_{i,TED} \quad (22)$$

$$\Delta F_t^{i,c} = \beta_{HKM}(-HKM_t) \times \text{sign}(F_{t-1}^{i,c}) + \lambda_{HKM} F_{t-1}^{i,c} + \eta_{i,HKM} \quad (23)$$

where $F_t^{i,c}$ is the net futures positioning of investor category c in index i at time t, ΔVIX_t and ΔTED_t are innovations to the TED spread and the VIX, HKM_t is the intermediary capital risk factor from He et al. (2017), and the η terms are asset fixed effects. The betas in the regression are the coefficients of interest. The regressions capture whether, in aggregate, investors in a particular category expand (positive beta) or contract (negative beta) their positions in response to deteriorating funding conditions.

Table 12 reports the results. For dealer net positioning, the coefficients are negative, but insignificant. If funding liquidity shocks correspond with futures supply being withdrawn, we expect a negative coefficient for dealer net futures positioning. The regressions also present evidence that hedge funds reduce their net futures positions corresponding with volatility shocks (t-statistic of -3.22) and with shocks to the intermediary capital risk factor (t-statistic of -3.09).[19] These results are reminiscent of the result in Brunnermeier et al. (2008), who suggest that speculators executing the carry trade in currencies unwind their positions during deteriorating financial conditions. Contraction in the net positions of hedge funds may be a reason that the LMH liquidity demand strategies do not appear strongly related to volatility and funding liquidity shocks. The LMH liquidity demand strategies take positions opposite hedge fund and institutional investor positioning. If hedge funds liquidate their positions (which would be consistent with de-risking when funding liquidity and volatility shocks hit), investors with positions opposite hedge funds may actually be buoyed by the liquidation of hedge fund net positions. Reductions in equity demand are also broadly consistent with volatility shocks and funding liquidity shocks reflecting bad times. However, the effects are not strong enough that the LMH strategies actually perform better in periods of deteriorating conditions, suggesting the shocks likely also affect liquidity providers in the stock market, whose positions we do not observe.

Our results highlight that both demanders and suppliers of equity index liquidity are likely to be affected by aggregate funding conditions. Volatility shocks and funding shocks likely correspond with the withdrawal of liquidity supply by liquidity providers and futures dealers, but likely also correspond with reductions in demand for equity exposure from futures end-users. In sum, these effects may cancel out, which can lead to the weak relationship we observe between the LMH Liquidity Demand strategy returns and proxies for funding liquidity and volatility shocks. More broadly, the results echo the discussion in He et al. (2017), that the relationship between financial

[19]Lagged futures positions are also highly statistically significant, suggesting weekly reversion in net positioning by each investor category, which is to be expected in a liquidity provision story.

intermediaries and asset prices may vary for different types of intermediaries. For example, debt-constrained "hedge funds" may have procyclical leverage in equilibrium, while equity-constrained commercial "banks" may face countercyclical leverage.

7 Conclusion

We show that violations of the law of one price convey more than just intermediation costs, offering information about liquidity demand in equity futures markets. Consistent with this notion, we find that bases between futures and spot prices negatively predict returns in futures and spot markets *in the same direction*, distinct from futures market and spot market prices merely converging. Bases appear to capture futures demand from hedge funds and institutional investors, with the associated return predictability compensating liquidity providers for meeting this demand.

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 means that deviations from covered interest rate parity contain information relevant for exchange rates, a point also made in Liao and Zhang (2020) and Greenwood et al. (2020), the latter also connecting the results with global bond markets. The supply and demand imbalance captured by bases also have implications for interpreting the interest rates embedded in derivatives prices (e.g., as studied by Binsbergen et al. (2019)), which we discuss further in Internet Appendix A.7. The results suggest that in addition to reflecting financial frictions, the demand captured by deviations from the law of one price may contain additional economic insights.

Tables and Figures

Figure 1: **Mechanics of Futures Trading**

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

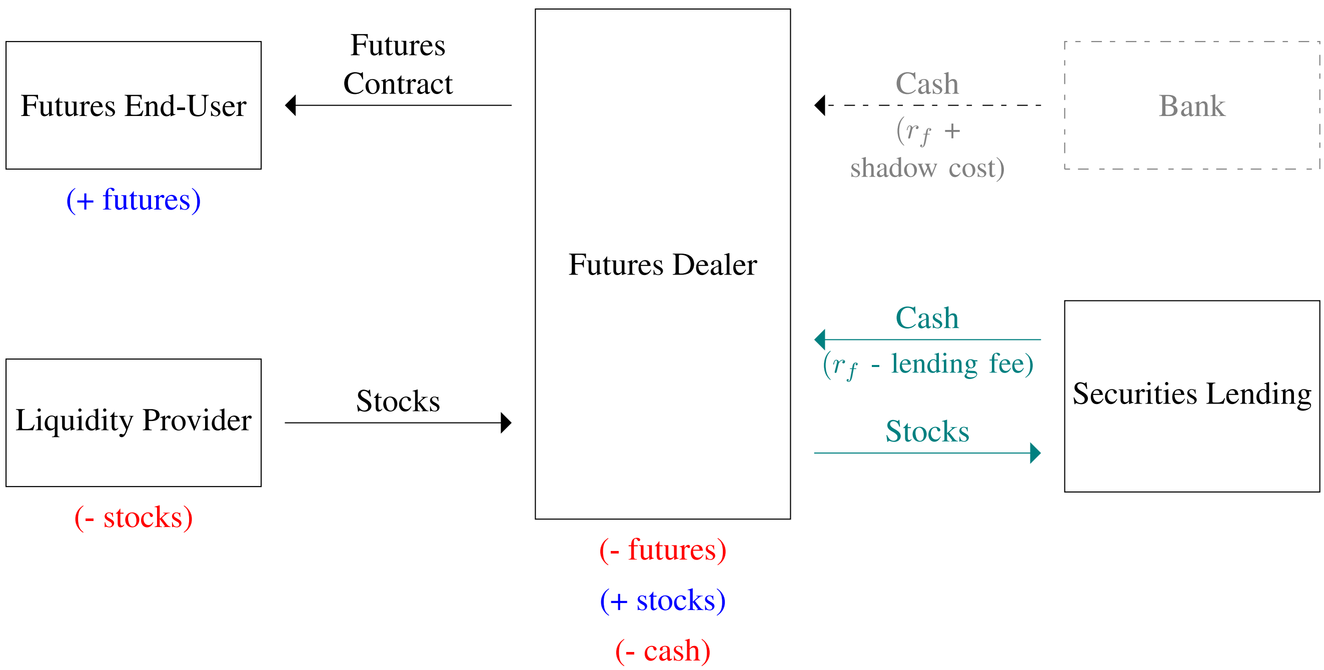


Figure 2: **Net Positioning from Traders in Financial Futures Report**

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

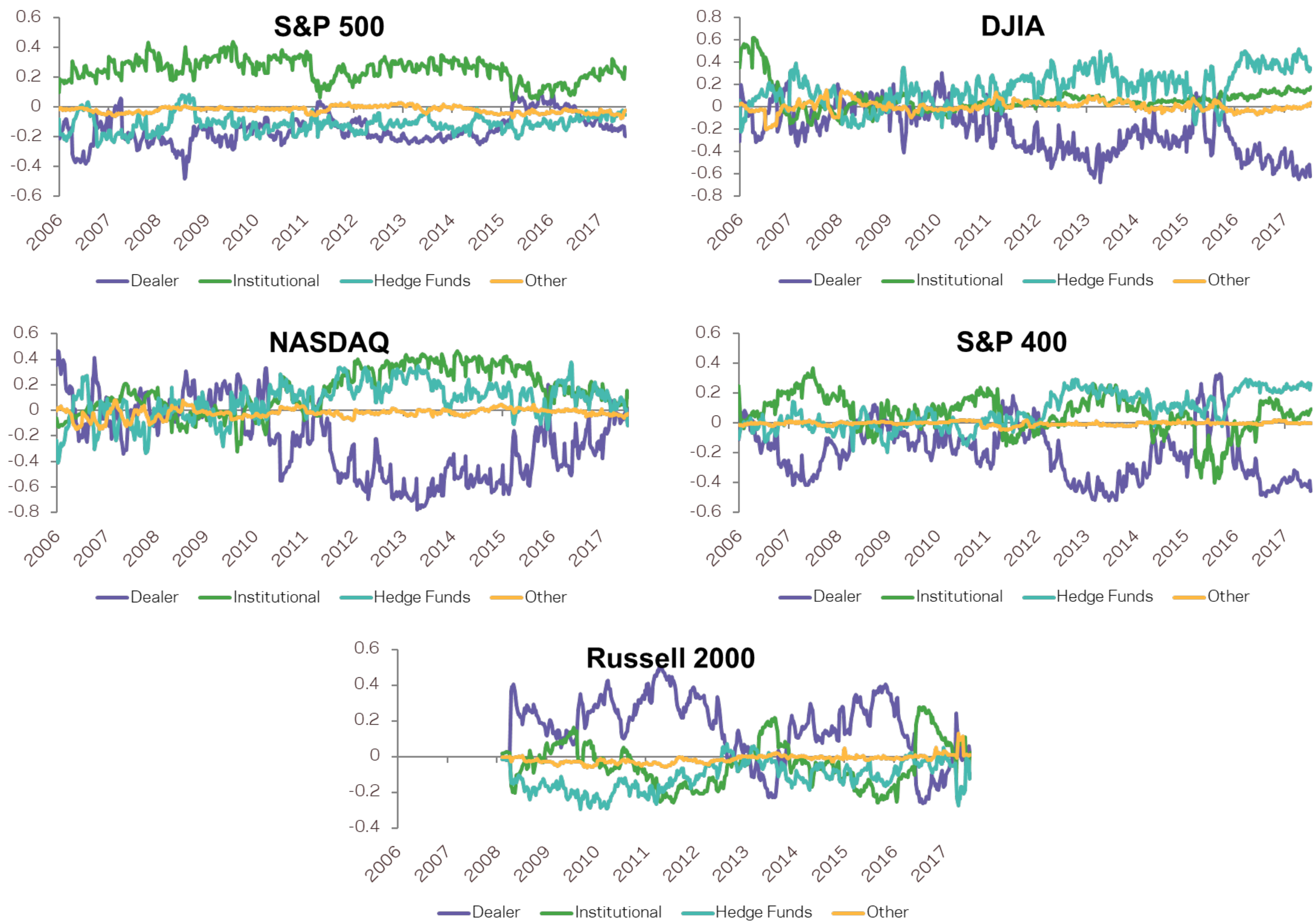
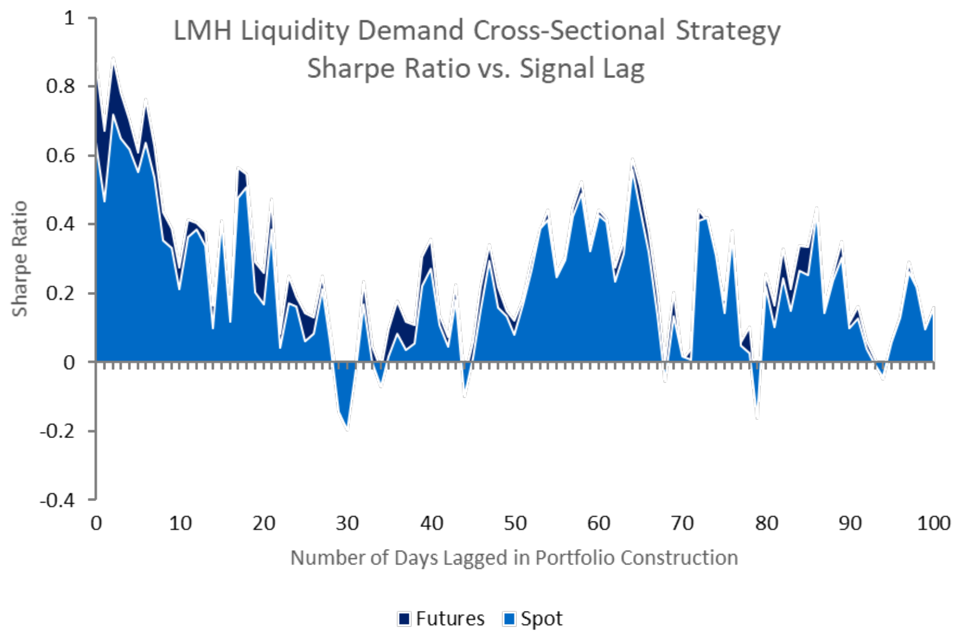


Figure 3: **Signal Lagging and Strategy Performance**

The figure plots the Sharpe ratio of LMH Liquidity Demand portfolios. The portfolios are formed following Equation (18) and Equation(20), where the signals are constructed by using an n-day lagged futures-spot basis (in addition to the one-day implementation lag in the main specification). The x-axis in the figure corresponds with different values of n and the y-axis corresponds with the Sharpe ratio of returns. Results are presented for trading strategies exclusively trading in futures and trading strategies exclusively trading in the spot market. The first plot corresponds with the cross-sectional strategy and the second plot corresponds with the timing strategy.



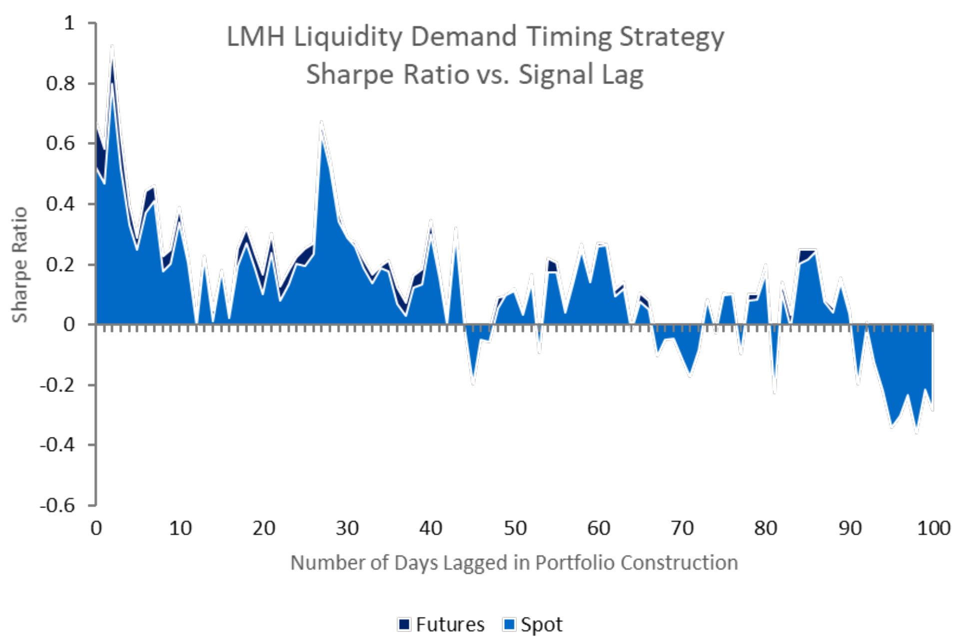
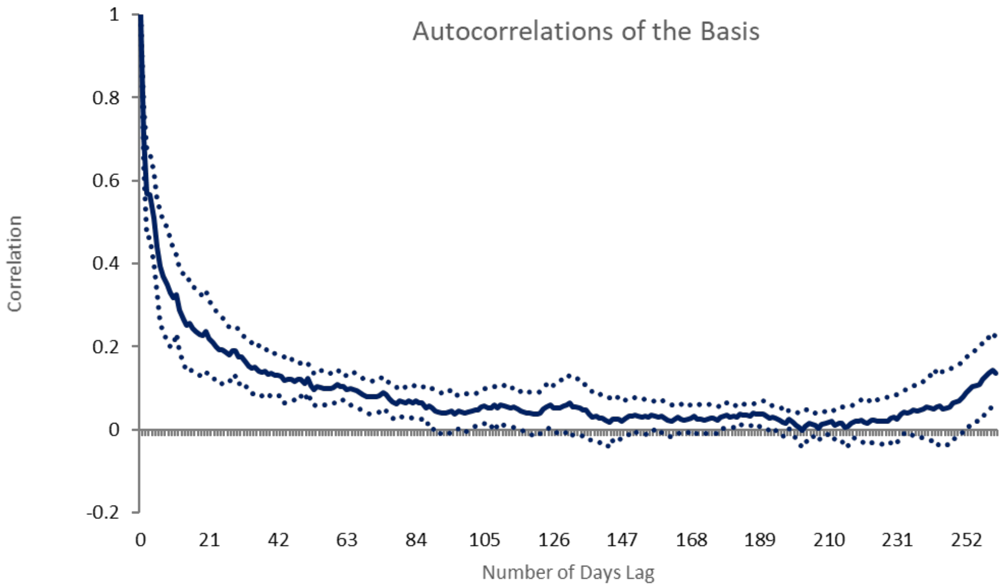


Figure 4: **Autocorrelations of the Basis and Dealer Positions**

The first plot in the figure displays the daily autocorrelation function of the basis in global equity markets, estimated from January 2000 through December 2017. The second plot in the figure displays the weekly autocorrelation function of dealer positions in US equity index futures markets, estimated from June 2006 through December 2017. For both plots, the values are calculated via a univariate panel regression of the variable of interest on lagged values of the variable, including entity-fixed effects. Standard errors are clustered by index and time. The dotted lines represent the 95% confidence interval for the autocorrelation coefficients.



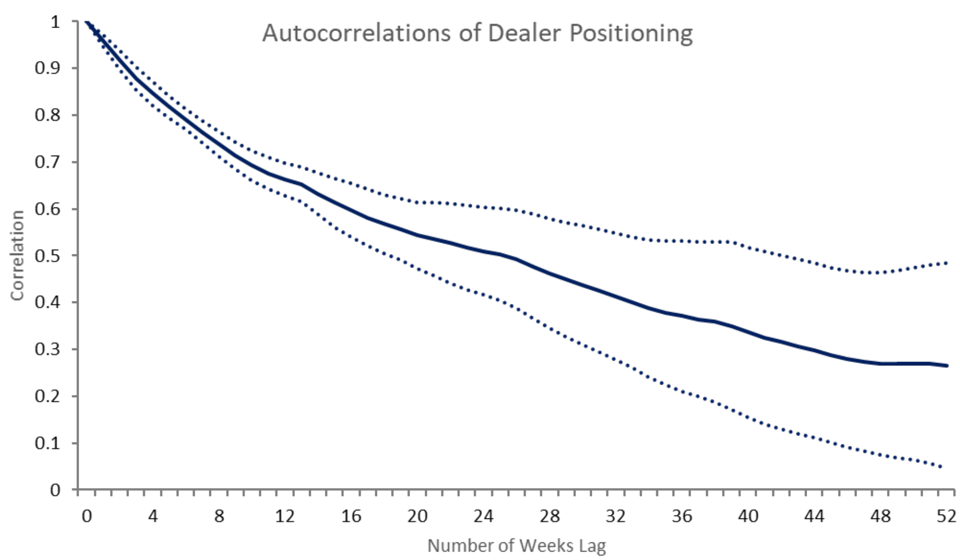


Table 1: **Basis Summary Statistics**

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

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

Table 2: **Correlation of Net Positioning by Investor Type**

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

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

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

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

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

Table 3: **Regression of Futures-Spot Basis on Investor Net Positioning in Futures**

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

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

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

Table 4: **Contemporaneous Relationship Between the Basis and Returns**

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

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

where $r^i_{t:t+1}$ is the return of asset i from period t to period $t+1$, a^i is the asset-specific intercept (or fixed effect), b_t are time-fixed effects, $\Delta x_{i,t}$ is the change in the variable x for index i from the previous period, and c and γ are the coefficient of interest that measure the contemporaneous relationship between the independent variable and market returns. Panel A reports the results for regressions where the independent variable is the futures-spot basis. Panel B reports the results for regressions where the independent variable is the net positioning of investor categories, with the independent variable scaled to have zero mean and unit standard deviation. The regression in Panel B only contains the US equity indices in the sample. The basis is measured in annualized percentage points. Returns are multiplied by 100. Observations are sampled weekly. Standard errors are clustered by time and entity. t-statistics are reported in parentheses.

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	0.44^{***}	0.44^{***}	0.17^{***}	0.17^{***}	0.41^{***}	0.41^{***}	0.13^{***}	0.13^{***}
	(5.25)	(5.25)	(5.39)	(5.39)	(4.99)	(4.99)	(3.91)	(3.91)
R^2	0.03	0.03	0.71	0.71	0.02	0.02	0.71	0.71
Observations	15522	15522	15522	15522	15522	15522	15522	15522
Time FE	No	No	Yes	Yes	No	No	Yes	Yes
Entity FE	No	Yes	No	Yes	No	Yes	No	Yes

Panel B: Contemporaneous Relationship Between Returns and Futures Positions

	Futures Market Returns				Spot Market Returns			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta F_t^{\text{Dealer}}$	-0.15^{**}				-0.14^{**}			
	(-3.16)				(-3.08)			
$\Delta F_t^{\text{Institutional}}$		0.15^{***}				0.14^{***}		
		(7.14)				(6.99)		
$\Delta F_t^{\text{Hedge Fund}}$			0.07				0.07	
			(1.54)				(1.45)	
$\Delta F_t^{\text{Other}}$				-0.01				-0.00
				(-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

t statistics in parentheses

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

Table 5: **Basis Return Predictability**

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

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

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

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 the period t, a^i is the asset-specific intercept (or fixed effect), b_t are time-fixed effects, and c and γ are the coefficient of interest that measure the predictive relationship between the independent variable and equity market returns. Panel A reports the results for regressions where the independent variable is the futures-spot basis, scaled to be in basis points per week. Panel B reports the results for regressions where the independent variable is the net positioning of different investor categories, scaled to have zero mean and unit standard deviation. Returns in both sets of regressions are scaled to be in basis points. The regression in Panel B only contains the US equity indices in the sample. Observations are sampled weekly. Standard errors are clustered by time and entity. t-statistics are reported in parentheses.

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

t statistics in parentheses

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

Table 6: **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 with the cross-sectional LMH Leverage Demand portfolios ("LMH Liquidity Demand XS") and the LMH Leverage Demand timing portfolios ("LMH Liquidity Demand TS"), implemented via futures contracts and in the spot market. Panel A reports the statistics for weekly rebalanced one-week reversal strategies (cross-sectional and time-series) and Panel B reports the 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	0.28%	14.64%	21.52%	0.52	4.10	0.68
Spot Returns	LMH Liquidity Demand XS	0.10%	5.22%	8.36%	0.17	3.71	0.62
	LMH Liquidity Demand TS	0.22%	11.31%	21.25%	0.36	3.88	0.53
Futures Returns	1-Week Reversal XS	0.16%	8.07%	10.41%	0.62	3.36	0.78
	1-Week Reversal TS	0.34%	17.60%	32.32%	-0.44	8.98	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%	17.21%	32.13%	-0.40	8.58	0.54

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	0.55%	6.59%	17.11%	0.27	1.39	0.39
Spot Returns	LMH Liquidity Demand XS	0.42%	5.01%	7.01%	0.51	2.60	0.72
	LMH Liquidity Demand TS	0.45%	5.44%	17.12%	0.26	1.32	0.32
Futures Returns	1-Month Reversal XS	0.21%	2.56%	8.77%	0.28	2.50	0.29
	1-Month Reversal TS	-0.89%	-10.69%	27.14%	-0.29	2.16	-0.39
Spot Returns	1-Month Reversal XS	0.20%	2.41%	8.84%	0.40	3.05	0.27
	1-Month Reversal TS	-0.90%	-10.82%	27.04%	-0.25	2.10	-0.40

Table 7: **LMH Liquidity Demand Exposure to Other Factors**

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

	Futures Returns		Spot Returns	
	XS	TS	XS	TS
Value	0.10	0.13	0.12	0.16
	(1.33)	(0.72)	(1.59)	(0.94)
Momentum	0.18**	0.57***	0.20***	0.58***
	(2.48)	(3.35)	(2.72)	(3.40)
Carry	0.01	-0.02	0.02	-0.00
	(0.47)	(-0.24)	(0.75)	(-0.06)
TSMOM	-0.01	-0.23***	-0.01	-0.23***
	(-0.35)	(-4.27)	(-0.49)	(-4.38)
PassiveLong	-0.02	0.27***	-0.02	0.26***
	(-0.52)	(3.61)	(-0.48)	(3.61)
1W Reversal-XS	-0.00		-0.02	
	(-0.05)		(-0.28)	
1W Reversal-TS		0.14***		0.14***
		(2.98)		(2.95)
α	0.56***	1.18***	0.41**	0.91**
	(3.44)	(3.07)	(2.49)	(2.39)
R^2	0.04	0.18	0.05	0.19
IR	0.86	0.76	0.62	0.59

t statistics in parentheses

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

Table 8: **The Futures-Spot Basis, Securities Lending, and Futures Positions**

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

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

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

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

Table 9: **Fund Flows, the Basis, and Investor Positioning**

The table reports statistics from panel regressions where the dependent variable is the weekly flows into mutual funds and ETFs that list a given index as their benchmark. Panel A reports results from regressions where the dependent variable is the one week change in the five-day rolling average of the basis. Panel B reports results from regressions where the dependent variable is the change in net positioning of futures dealers. Panel C reports results from regressions where the dependent variable is the change in net positioning of Hedge Funds. Panel D reports results from regressions where 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 reported in parentheses.

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

t statistics in parentheses

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

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 10: **Futures-Spot Bases and Aggregate Funding Conditions**

The table displays regression results from time-series regressions of the changes in the magnitude of the futures-spot basis on shocks aggregate funding conditions. There are two proxies for changes in the magnitude of the futures-spot basis: the difference in the average absolute value of the basis across indices at time t and $t-1$, and the difference in the cross-sectional standard deviation of the basis across indices at time t and $t-1$. Shocks to aggregate funding conditions are measured via the returns of the intermediary capital risk factor (He et al. (2017)), innovations to the Treasury minus Eurodollar (TED) spread, and innovations to the VIX. Independent variables in the regression are scaled to have zero mean and unit standard deviation. Observations are sampled weekly.

	Δ Absolute Basis$_t$			Δ Basis XS STD$_t$		
	HKM	ΔTED$_t$	ΔVIX$_t$	HKM	ΔTED$_t$	ΔVIX$_t$
Intercept	-0.24	-0.22	-0.21	-0.47	-0.45	-0.45
	-(0.27)	-(0.25)	-(0.24)	-(0.22)	-(0.21)	-(0.21)
Beta	3.93	4.35	4.96	3.22	8.64	6.39
	(4.46)	(5.00)	(5.68)	(1.51)	(4.13)	(3.02)
N	927	927	927	927	927	927
R^2	0.02	0.03	0.03	0.00	0.02	0.01

Table 11: **LMH Liquidity Demand Strategies, Liquidity and Volatility**

The table reports the alphas and betas from regressions of the weekly returns of the LMH Liquidity Demand strategies on measures related to liquidity provision. The measures include the intermediary capital ratio factor from He et al. (2017), the Treasury Minus Eurodollar (TED) Spread, the lagged level of the VIX, and changes in the VIX. Independent variables are signed such a positive coefficient corresponds with the strategy performing worse coincident with deteriorating conditions, and performs better when the level of the VIX is high in the previous period. Returns in the regression are multiplied by 100. t-statistics are reported in parentheses. The regressions in Panel A are univariate regressions, while the regressions in Panel B include the returns of an equally weighted basket of the equity indices in the sample, rebalanced weekly, as a control.

Panel A: Loadings on Liquidity Variables, No Market Control

	Timing Strategies								Cross-Sectional Strategies							
	Futures				Spot				Futures				Spot			
	HKM	TED	VIX	ΔVIX	HKM	TED	VIX	ΔVIX	HKM	TED	VIX	ΔVIX	HKM	TED	VIX	ΔVIX
Intercept	0.29	0.28	0.27	0.27	0.23	0.21	0.21	0.21	0.13	0.14	0.14	0.14	0.10	0.10	0.10	0.10
	(2.97)	(2.88)	(2.80)	(2.87)	(2.37)	(2.24)	(2.19)	(2.22)	(3.44)	(3.65)	(3.66)	(3.65)	(2.49)	(2.65)	(2.72)	(2.66)
β	0.68	0.47	0.07	0.55	0.64	0.44	0.04	0.52	0.00	-0.05	-0.01	-0.03	-0.03	-0.04	-0.04	-0.05
	(6.99)	(4.41)	(0.77)	(5.97)	(6.60)	(4.16)	(0.40)	(5.68)	(0.07)	(-1.13)	(-0.38)	(-0.79)	(-0.69)	(-1.00)	(-1.05)	(-1.42)

Panel B: Loadings on Liquidity Variables with Market Control

	Timing Strategies								Cross-Sectional Strategies							
	Futures				Spot				Futures				Spot			
	HKM	TED	VIX	ΔVIX	HKM	TED	VIX	ΔVIX	HKM	TED	VIX	ΔVIX	HKM	TED	VIX	ΔVIX
Intercept	0.30	0.28	0.27	0.28	0.24	0.21	0.21	0.22	0.13	0.14	0.14	0.14	0.10	0.10	0.10	0.10
	(3.06)	(2.98)	(2.92)	(2.98)	(2.45)	(2.31)	(2.28)	(2.32)	(3.44)	(3.62)	(3.64)	(3.63)	(2.49)	(2.61)	(2.68)	(2.62)
β	-0.03	0.31	0.06	-0.19	-0.06	0.28	0.03	-0.20	0.00	-0.05	-0.01	-0.04	-0.02	-0.04	-0.04	-0.05
	(-0.18)	(2.91)	(0.68)	(-1.33)	(-0.41)	(2.69)	(0.30)	(-1.41)	(0.04)	(-1.06)	(-0.38)	(-0.66)	(-0.37)	(-0.82)	(-1.06)	(-0.85)

Table 12: **Investor Positioning, Funding Liquidity Shocks, and Volatility Shocks**

The table reports the results from panel regressions of changes in net futures positioning on the intermediary capital risk factor from He et al. (2017), innovations in the VIX and innovations in the TED spread, interacted with the sign of futures positioning in the previous period. Observations are weekly. t-statistics are reported in parentheses. Standard errors are clustered by entity and time.

	$\Delta F_t^{\text{Dealer}}$			$\Delta F_t^{\text{Hedge Fund}}$			$\Delta F_t^{\text{Institutional}}$			$\Delta F_t^{\text{Other}}$		
$\Delta VIX_t \times \text{sign}(F_{t-1})$	-0.03			-0.09**			-0.06			0.01		
	(-0.77)			(-3.22)			(-0.79)			(0.67)		
$\Delta TED_t \times \text{sign}(F_{t-1})$		-0.03			-0.02			-0.06			-0.01	
		(-0.78)			(-0.91)			(-2.10)			(-0.73)	
$HKM_t \times \text{sign}(F_{t-1})$			-0.02			-0.07**			-0.04			0.01
			(-0.51)			(-3.09)			(-0.58)			(0.34)
F_{t-1}	-0.17***	-0.17***	-0.17***	-0.25***	-0.25***	-0.25***	-0.18***	-0.18***	-0.18***	-0.21***	-0.21***	-0.21***
	(-5.52)	(-5.38)	(-5.43)	(-6.06)	(-6.10)	(-6.34)	(-5.50)	(-5.42)	(-5.52)	(-24.21)	(-24.02)	(-23.85)
R^2	0.02	0.02	0.02	0.04	0.03	0.04	0.02	0.02	0.02	0.04	0.04	0.04
Observations	2874	2874	2874	2874	2874	2874	2874	2874	2874	2874	2874	2874
Entity FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes				

t statistics in parentheses

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

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Internet Appendix for

Beyond Basis Basics: Liquidity Demand and Deviations from the Law of One Price

Todd M. Hazelkorn, Tobias J. Moskowitz, Kaushik Vasudevan

August 10, 2020

Contents

A.1 Proof of Informed Trader Demand

The expression and derivation are nearly identical to Nagel (2012). Because informed traders are myopic and have CARA utility, their demand function is linear in the expected dollar return of investing in futures:

$$y_t = \tilde{\beta}\left(E\left[P^f_{t+1}|\mathcal{I}_t\right] - E\left[P^f_t|\mathcal{I}_t\right]\right) \tag{24}$$

where $\mathcal{I}_t$ reflects the informed traders' information set at time t. Shocks are iid and each futures contract delivers a unit of the risky asset in period $t+1$, so $E\left[P^f_{t+1}|\mathcal{I}_t\right] = \left[P^s_{t+1}|\mathcal{I}_t\right] = v_t + s_t$. When submitting market orders, the informed traders accurately conjecture that their market impact per unit of order flow on futures will be $1/\gamma + \phi + c$ and that their aggregate demand is linear in their signal, $y_t = \beta s_t$. $1/\gamma + \phi$ is the market impact on the risky asset price and c is the additional market impact on futures prices. Hence,

$$E\left[P^f_t|\mathcal{I}_t\right] = v_t + \left(\frac{1}{\gamma} + \phi + c\right)\beta s_t \tag{25}$$

Substituting back into Equation (24) we have that

$$y_t = \tilde{\beta}\left(s_t - \left(\frac{1}{\gamma} + \phi + c\right)\beta s_t\right) \tag{26}$$

which is consistent with the conjecture that $y = \beta s_t$, with

$$\beta = \frac{\tilde{\beta}}{1 + \tilde{\beta}\left(1/\gamma + \phi + c\right)} \tag{27}$$

This is the same as the expression in Nagel (2012), with an added term that corresponds to informed traders internalizing how the balance sheet costs from their trading is incorporated into futures prices.

A.2 Basis Summary Statistics

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

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

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

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

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

A.3 Impact of Measurement of Dividends on Results

There are two notable obstacles we face in our construction of bases. First, we do not have data on expectations of dividends in the first part of the sample. Second, even when we do have estimates of expected dividends, our estimates correspond with estimates under the physical measure, while Equation (7) requires estimates of expected dividends under the risk-neutral measure. For the first issue, we use realized dividends to proxy for expected dividends. For the second issue, we use dividends under the physical measure to proxy for dividends under the risk neutral measure. The equity index futures contracts in our sample have maturities ranging from ten days to three months, and in all of the markets we consider, dividends are usually announced one-to-three months before dividend ex-date. Hence, we expect the majority of dividends for an index to be known in our calculation of the basis, mitigating concerns associated with the two issues.

We extensively analyze the impact of both modeling choices about dividends on our results and find that the effects are small. Internet Appendix A.3.1 provides evidence that dividends are generally announced one to three months in advance of dividend ex-date. Internet Appendix A.3.2 analyzes measurement error in the basis from our assumptions about dividends using two case studies. First, since the end of 2015, futures contracts on the quarterly dividends of the S&P 500 have traded on the Chicago Mercantile Exchange. We therefore use the dividend futures prices to provide a measure of dividend expectations under the risk neutral measure. We use risk-neutral dividend expectations from dividend futures prices to assess the impact of using dividends under the physical measure and realized dividends in the S&P 500 basis. Second, we study the basis in the German DAX index, which is a total return index. Because the DAX index is a total return index, the basis for the DAX is unaffected by measurement issues with dividend expectations. We compare the behavior of the basis of the DAX index to the behavior of the basis of the EUROSTOXX index; approximately 30% of the index weight of the EUROSTOXX index consists of German stocks in the DAX index, which makes it a close counterpart of the DAX index. In Internet Appendix A.3.3, we assess the impact of the use of physical expectations to proxy for risk-neutral expectations on our results relating the basis with returns. In Internet Appendix A.3.4, we compare how using realized dividends versus expectations of dividends from Goldman Sachs affects the estimated relationships between bases and returns in the sample from 2007 to 2017. We find that our treatment of dividends introduces a small amount of measurement error, but it does not meaningfully impact our results, and in some cases, the results suggest that our treatment of dividends may slightly understate the strength of our findings.

A.3.1 Dividend Announcement Dates and Ex-Dates

We provide evidence for the number of days between dividend announcement and dividend ex-date for stocks in the indices in our sample. We obtain data on dividend announcement and dividend ex-dates from Xpressfeed and Datastream for the companies that are part of the equity indices in our sample. Using these data, we calculate the average number of calendar days between dividend announcement and dividend ex-dates for each index, where each observation in the average corresponds with a single dividend paid by a company that is part of the index.

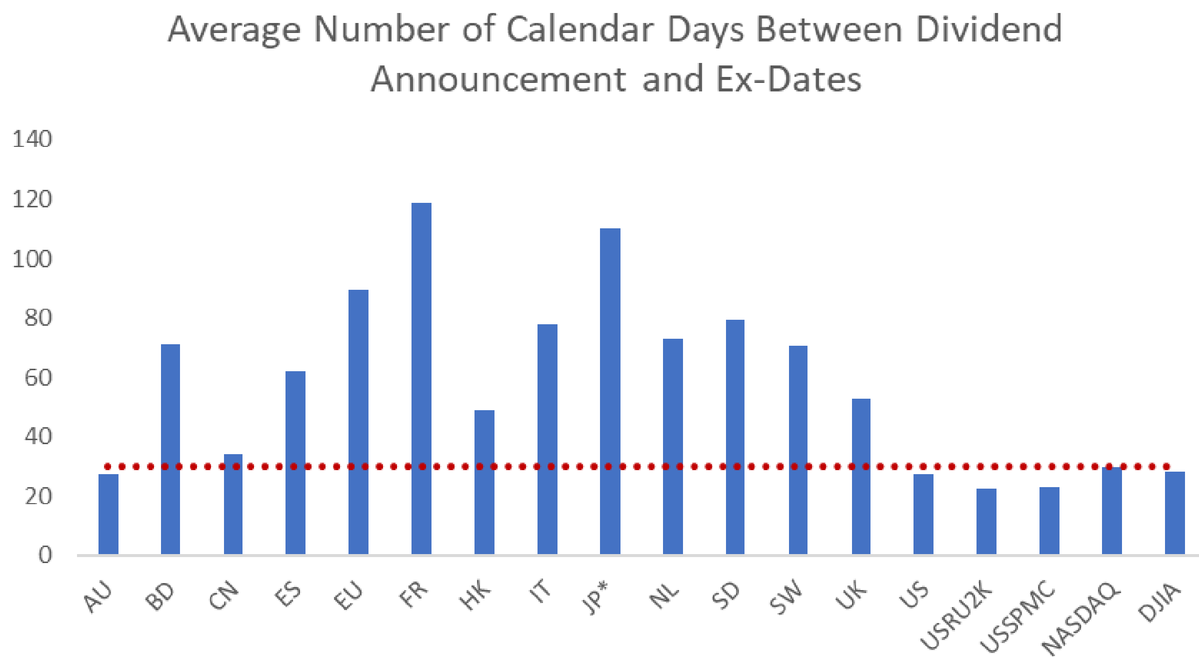
Figure A.1 plots the average number of calendar days between dividend announcement and ex-dates for each index in the sample. The figure also plots a dotted red line at 30 days. The average number of days ranges from approximately 22.5 days (for the Russell 2000 index) to approximately 120 days for the French CAC40 index. With the exception of the Australian index, the average time between dividend announcement and dividend ex-date is more than 30 days for non-US indices, and often more than two months for European stocks. American companies and Australian companies announce dividends a little bit less than 30 days before dividend ex-date.

One reason for the difference in the length between dividend announcement and dividend ex-dates across indices comes from differences in how often companies pay dividends. In European countries, for example, the norm in our sample is to pay dividends semi-annually or annually. US companies often pay quarterly or even monthly dividends, with the amount mostly remaining constant from quarter-to-quarter (or month-to-month). Generally, companies that pay dividends less often tend to have a wider gap between dividend announcement and dividend ex-dates.

A last idiosyncrasy for our sample is that in Japan, the common practice is to announce an *estimated* dividend amount on the announcement date. The announced amount is usually honored. However, the amount of the dividend payment is not usually confirmed until after dividend ex-date. In the figure, we show the number of days between the dividend ex-date and the initial dividend announcement date for Japan. On average, we find that dividends are confirmed a little less than 40 days after dividend ex-dates.

Figure A.1: **Dividend Announcement and Ex-Dates**

The figure plots the average number of calendar days between dividend announcement and dividend ex-date for the indices in our sample. The data used in the calculation are from Xpressfeed and Datastream. For each index, the average is calculated where each observation corresponds with a single dividend paid out by a company that is a part of the index. The dotted red line corresponds with thirty calendar days.



A.3.2 Two Case Studies on the Impact of Dividend Assumptions

We present two case studies of the basis that suggest that the impact of our assumptions about dividends are likely to be small. First, since December of 2015, listed futures on the quarterly dividends of the S&P 500 have traded on the Chicago Mercantile Exchange. These futures contracts allow us to directly observe the risk-neutral expectations of S&P 500 dividends required to satisfy Equation (7).[20] In Figure A.2, we plot the annualized expected dividend used in the calculation of the basis for the S&P 500, $E_t(D_{t+1})/S_t$ from January 2016 to March 2020. The figure plots the expected dividend yield calculating using risk-neutral dividend expectations, dividend expectations from Goldman-Sachs, and the realized dividends over the lifetime of the futures contracts. The lines lie on top of each other, and are generally quite similar, though not identical, with differences usually occurring near futures expiration dates. The average difference and average absolute difference between the basis calculated using dividend expectations under the physical measure and the basis calculated using dividend expectations under the risk-neutral measure are 0.6 basis points and 4.3 basis points. The average difference and average absolute difference between the basis calculated using expectations under the risk-neutral measure and the basis calculated using realized dividends are 1.6 basis points and 4.3 basis points. Compared with the average absolute value of and the time-series standard deviation the basis of 22 basis points and 31 basis points reported for the S&P500 in Table A.1, these numbers suggest that there may be some measurement error coming from the treatment of dividends, but the error is small compared with variation in the basis.

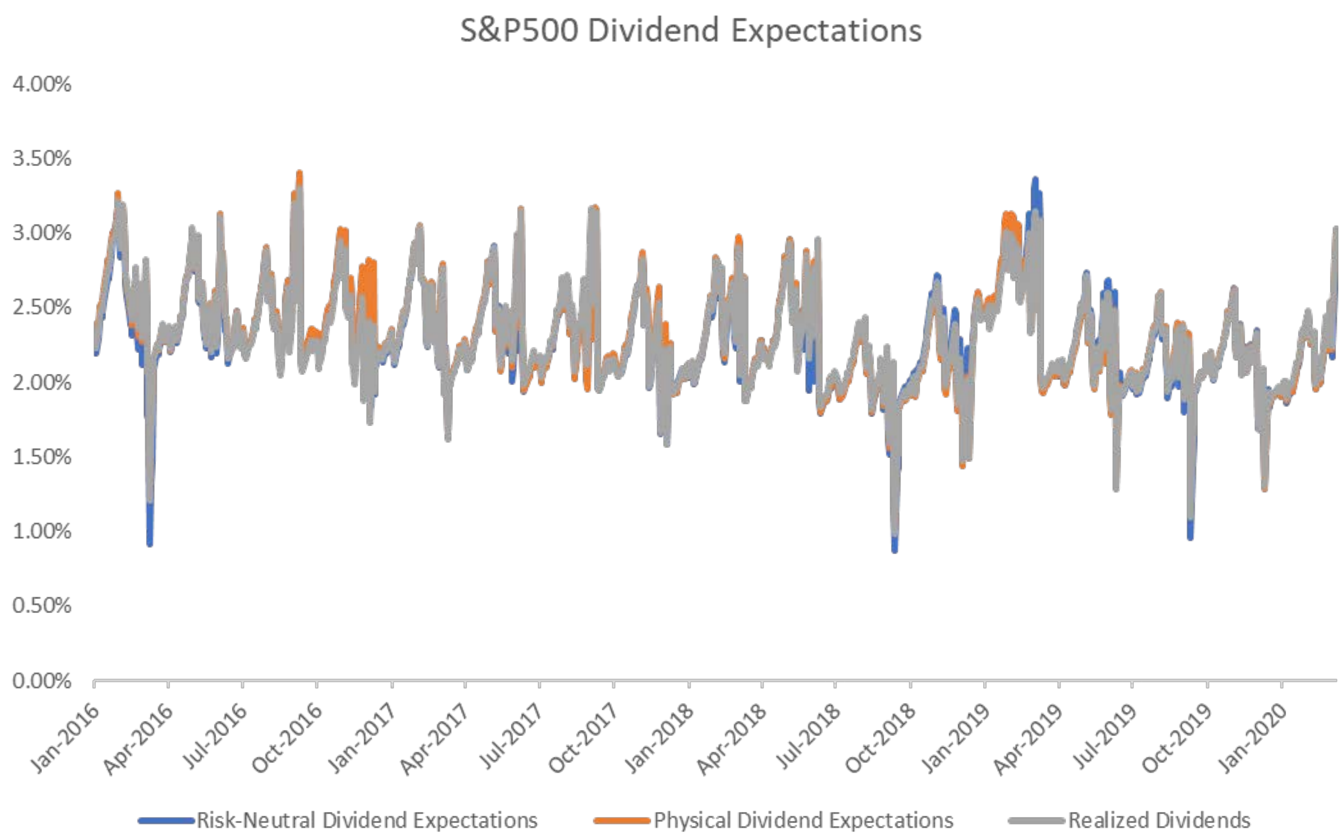
Second, our sample contains the German DAX index, which is unique in that it is a total return index. The level of the index is constructed by assuming that all dividends are reinvested. This means, in calculating the fair-value of a futures contract, there is no need to subtract the risk-neutral expectation of dividends in Equation (7), and there is no measurement issue in the basis coming from the treatment of dividends. Looking to the asset-by-asset summary statistics for the basis presented in Table A.1, we observe that the time-series standard deviation of the basis for the DAX is 57 basis points, and the average absolute basis is 32 basis points. We can compare these numbers with the same numbers for the closest counterpart to the DAX index in our sample, the

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

EUROSTOXX index, which is a broad-based index that contains Eurozone stocks. In our sample, approximately 30% of the index weight of the EUROSTOXX comes from German stocks that are also in the DAX index. The time-series standard deviation of the basis for the EUROSTOXX index is 57 basis points and the average absolute basis is 35 basis points. In the sample for which we have data for both the EUROSTOXX and the DAX (the EUROSTOXX index starts in 2001), the average of the basis is 4 basis points for the DAX and 10 basis points for the EUROSTOXX. The magnitude and behavior of the basis is quite similar for the DAX and EUROSTOXX indices, suggesting that there is not a clear or large bias stemming from our assumptions about dividends for the EUROSTOXX index.

Figure A.2: **S&P500 Dividend Expectations**

The figure plots the annualized expected dividend yield for a futures contract used in the calculation of the basis, defined as the expectation of index dividends divided by the spot price, using three different methods of calculation for the S&P500. The first blue line corresponds with dividend expectations under the risk-neutral, which are extracted from the prices of quarterly dividend futures. The second orange line corresponds with dividend expectations under the physical measure, which are provided by Goldman Sachs. The third gray line plots the realized dividends.



A.3.3 Expectations of Dividends Under the Physical Versus Risk-Neutral Measure and Returns

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

Binsbergen and Koijen (2017) calculate that the monthly holding period returns of one-year maturity dividend strips range from 41 basis points (for the S&P 500) to 1.1 percent (for the Japanese Nikkei index), which are broadly in line with Binsbergen et al. (2012). These estimates present a conservative upper bound for the risk premium we expect to be embedded in the dividend expectations of the futures contracts used in our sample. The equity index futures contracts in our sample have maturities ranging from ten days to three months. As we show in the internet appendix, in all of the markets that we consider, dividends are announced approximately one to three months prior to the dividend ex-date. Therefore, we expect the majority of dividends for an index to be known in our calculations of the basis (and thus have little risk premium associated with them). Put differently, we expect the majority of the risk premium earned in the one-year maturity dividend strips analyzed by Binsbergen and Koijen (2017) to be earned on ex-dividends beyond the maturity of the contracts that we use in the calculation of bases. The case studies in Section A.3.2 suggest that the magnitude of error introduced in our calculations of the basis may be around one to five basis points, which are small in comparison to the bases we measure. The numbers also imply much smaller dividend risk premium embedded in the very short maturity contracts we analyze, compared to those studied in Binsbergen and Koijen (2017).

Nevertheless, we conduct additional analysis on the impact that potentially larger dividend risk premia may have on our results. To do so, we calculate the basis under various assumptions for the dividend risk premium, which for simplicity, we assume to be constant over time and across indices. For each day and each futures contract in our sample from 2000-2017, we calculate the annualized difference in the futures-spot basis that come from dividend risk premia by using the amount of ex-dividends expected until expiration and our assumed level of dividend risk premia. Subtracting these estimates from the futures-spot basis for each contract, we reconstruct the index level basis series for each equity index and rerun our tests.

For the sample from January 2000 to December 2017, we re-run the regressions in Table 4 using the basis series constructed with various dividend risk premium estimates. We use monthly dividend risk premia estimates of 0 bps (the baseline estimates reported in the main paper), 20 bps, 50 bps, 80 bps, 110 bps. The results are reported in Table A.3. The regression coefficients are broadly similar. The t-statistics actually increase as we increase the estimated dividend risk premium. Differences in dividends across time for the same index capture stocks going ex-dividend. The regression results may be picking up on well documented dividend ex-date effects, whereby the stock prices do not drop by the full amount of the dividend (e.g. Grinblatt et al. (1984)). This would be consistent with the stronger contemporaneous basis-return relationship we observe as we increase the assumed dividend risk premium.

From January 2000 to December 2017, we rerun the return predictability regressions from Table 5 using our basis series constructed under the various dividend risk premia estimates. Table A.4 reports the results from these regressions. The regression coefficients are broadly similar under various dividend risk premia assumptions. Return predictability becomes slightly stronger as we increase the magnitude of the dividend risk premia. Increasing the dividend risk premia estimate for an equity index makes the basis we estimate more correlated with the index's "carry" (defined as the normalized difference between the futures and spot price of the index), from Koijen et al. (2018), which also has strong return predictability.

We also form cross-sectional and timing trading strategies using the newly constructed futures-spot basis series. Table A.5 reports the annualized return statistics for these portfolios. For the cross-sectional strategies, when implemented in futures markets, the performance decays slightly, but annualized Sharpe ratios remain above 0.78 in all specifications. In the spot market, Sharpe ratios are all above those reported in the baseline specification. For the timing strategies, the alternative strategies all have slightly higher Sharpe ratios than the main specification.

The analysis suggests that the time-series and cross-sectional return predictability of the futures-spot basis are not largely affected by assumptions about dividend risk premia.

Table A.3: **Contemporaneous Relationship Between the Basis and Returns under Dividend Risk Premia Assumptions**

The table reproduces the regressions in Panel A of Table 4, using futures-spot basis series that are constructed by making assumptions about the size of monthly dividend risk premia. Each row labeled x corresponds with the basis constructed assuming a monthly dividend risk premium of x basis points.

	Futures Market Returns				Spot Market Returns			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
0	0.44***	0.44***	0.17***	0.17***	0.41***	0.41***	0.13***	0.13***
	(5.25)	(5.25)	(5.39)	(5.39)	(4.99)	(4.99)	(3.91)	(3.91)
20	0.46***	0.46***	0.18***	0.18***	0.42***	0.42***	0.14***	0.14***
	(4.80)	(4.80)	(6.51)	(6.51)	(4.64)	(4.64)	(4.69)	(4.69)
50	0.46***	0.46***	0.19***	0.19***	0.43***	0.43***	0.15***	0.15***
	(4.69)	(4.69)	(6.50)	(6.50)	(4.53)	(4.53)	(4.80)	(4.81)
80	0.46***	0.46***	0.19***	0.19***	0.43***	0.43***	0.15***	0.15***
	(4.66)	(4.66)	(6.45)	(6.44)	(4.50)	(4.50)	(4.86)	(4.86)
110	0.45***	0.45***	0.18***	0.18***	0.42***	0.42***	0.15***	0.15***
	(4.70)	(4.70)	(6.40)	(6.39)	(4.53)	(4.53)	(4.88)	(4.88)
Time FE	No	No	Yes	Yes	No	No	Yes	Yes
Entity FE	No	Yes	No	Yes	No	Yes	No	Yes

t statistics in parentheses

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

Table A.4: **Global Equities Basis Return Predictability Under Dividend Risk Premia Assumptions**

The table reproduces the regressions in Panel A of Table 5, using futures-spot basis series that are constructed by making assumptions about the size of monthly dividend risk premia. Each row labeled x corresponds with the basis constructed assuming a monthly dividend risk premium of x basis points.

	Futures Market Returns				Spot Market Returns			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
0	-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)
20	-4.84***	-4.22***	-4.91***	-4.18***	-3.34**	-2.66**	-3.34*	-2.54**
	(-3.03)	(-4.40)	(-2.93)	(-4.36)	(-2.19)	(-2.54)	(-2.08)	(-2.39)
50	-5.26***	-4.35***	-5.38***	-4.38***	-3.78**	-2.82**	-3.83**	-2.74**
	(-3.35)	(-4.60)	(-3.23)	(-4.60)	(-2.53)	(-2.69)	(-2.42)	(-2.60)
80	-5.48***	-4.34***	-5.68***	-4.44***	-4.09**	-2.87**	-4.19**	-2.86**
	(-3.51)	(-4.67)	(-3.37)	(-4.66)	(-2.74)	(-2.78)	(-2.61)	(-2.74)
110	-5.52***	-4.19***	-5.78***	-4.37***	-4.24**	-2.83**	-4.40**	-2.89**
	(-3.55)	(-4.64)	(-3.39)	(-4.63)	(-2.83)	(-2.82)	(-2.70)	(-2.80)
Time FE	No	Yes	No	Yes	No	Yes	No	Yes
Entity FE	No	No	Yes	Yes	No	No	Yes	Yes

t statistics in parentheses

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

Table A.5: **Global Equity LMH Leverage Demand Strategy Performance by Dividend Risk Premium Assumption**

The table displays statistics of the returns of the LMH Liquidity Demand strategies constructed by making assumptions about the size of the dividend risk premium used in the calculation of the basis. Panel A presents results for the cross-sectional LMH Liquidity Demand strategy implemented in futures markets. Panel B presents results for the cross-sectional LMH Liquidity Demand strategy implemented in spot markets. Panel C presents results for the LMH Liquidity Demand timing strategy implemented in futures markets. Panel D displays results for the LMH Liquidity Demand timing strategy implemented in spot markets.

Panel A: LMH Liquidity Demand Futures XS Strategy

Assumed Monthly Dividend Risk Premium (Basis Points)	Weekly Mean	Annualized Mean	Annualized Standard Deviation	Skewness	Kurtosis	Annualized Sharpe Ratio
0	0.14%	7.21%	8.40%	0.53	4.00	0.86
20	0.14%	7.35%	8.95%	0.51	5.84	0.82
50	0.14%	7.40%	8.90%	0.66	6.72	0.83
80	0.13%	6.87%	8.86%	0.71	7.02	0.78
110	0.13%	6.92%	8.90%	0.70	6.69	0.78

Panel B: LMH Liquidity Demand Futures XS Strategy

Assumed Monthly Dividend Risk Premium (Basis Points)	Weekly Mean	Annualized Mean	Annualized Standard Deviation	Skewness	Kurtosis	Annualized Sharpe Ratio
0	0.10%	5.22%	8.36%	0.17	3.71	0.62
20	0.11%	5.58%	8.67%	0.25	4.35	0.64
50	0.11%	5.75%	8.62%	0.33	4.66	0.67
80	0.10%	5.38%	8.60%	0.38	4.58	0.63
110	0.10%	5.45%	8.64%	0.38	4.31	0.63

Panel C: LMH Liquidity Demand Futures Timing Strategy

Assumed Monthly Dividend Risk Premium (Basis Points)	Weekly Mean	Annualized Mean	Annualized Standard Deviation	Skewness	Kurtosis	Annualized Sharpe Ratio
0	0.29%	15.11%	21.79%	0.60	4.31	0.69
20	0.30%	15.41%	22.69%	0.42	4.12	0.68
50	0.31%	16.14%	22.51%	0.46	4.30	0.72
80	0.32%	16.55%	22.22%	0.51	4.55	0.74
110	0.31%	16.33%	21.84%	0.52	4.89	0.75
140	0.31%	15.88%	21.26%	0.55	5.13	0.75

Panel D: LMH Liquidity Demand Futures Timing Strategy

Assumed Monthly Dividend Risk Premium (Basis Points)	Weekly Mean	Annualized Mean	Annualized Standard Deviation	Skewness	Kurtosis	Annualized Sharpe Ratio
0	0.22%	11.65%	21.48%	0.43	3.99	0.54
20	0.23%	12.04%	22.19%	0.31	3.66	0.54
50	0.25%	12.92%	22.00%	0.33	3.73	0.59
80	0.26%	13.50%	21.70%	0.37	3.84	0.62
110	0.26%	13.48%	21.30%	0.36	4.05	0.63
140	0.25%	13.25%	20.71%	0.37	4.17	0.64

A.3.4 Using Realized Dividends vs. Expected Dividends in Basis Construction

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

We re-run the regressions capturing the contemporaneous relationship between the basis and returns from Table 4 for the sub-sample from 2007-2017 using the dividend expectations from Goldman Sachs and using realized index dividends. Table A.6 reports the results from the regressions. The coefficients and t-statistics are very similar when using realized dividends and when using dividend expectations.

Next, we re-run the basis return predictability regressions reported in Table 5, for the sub-sample from 2007 to 2017, using both the dividend expectations from Goldman Sachs as well as realized dividends in the construction of the basis. The results are similar, though the coefficients and statistical significance are smaller when using realized dividends. This is consistent with the idea that the use of realized dividends might understate the predictive power the basis has for subsequent returns.

We also construct the LMH Liquidity Demand strategies using realized dividends and compare them to the strategies constructed using dividend expectations. The strategies constructed using realized dividends are highly correlated with the corresponding strategies constructed using dividend expectations (0.88 to 0.89), but the strategies constructed using realized dividends have lower returns on average (Table A.8). Once again, this is consistent with a slight understatement of the strategy's profitability when using realized as opposed to expected dividends.

Table A.6: **Contemporaneous Relationship Between Changes in the Basis and Returns, 2007-2017**

The table reproduces the regressions in Panel A of Table 4 using futures-spot basis series constructed using dividend expectations from Goldman Sachs ("Expected Dividends") and using the actual dividends that were paid out for each index ("Realized Dividends"). The sample period is January 2007 through December 2017.

	Futures Market Returns				Spot Market Returns			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Expected Dividends	0.69***	0.69***	0.24***	0.24***	0.64***	0.64***	0.19***	0.19***
	(4.20)	(4.20)	(4.86)	(4.86)	(4.10)	(4.10)	(3.67)	(3.67)
Realized Dividends	0.67***	0.67***	0.24***	0.24***	0.63***	0.63***	0.20***	0.20***
	(4.25)	(4.25)	(4.82)	(4.82)	(4.14)	(4.14)	(3.68)	(3.68)
Time FE	No	No	Yes	Yes	No	No	Yes	Yes
Entity FE	No	Yes	No	Yes	No	Yes	No	Yes

Table A.7: **Global Equities Basis Return Predictability, 2007-2017**

The table reproduces the regressions in Panel A of Table 5 using futures-spot basis series constructed using dividend expectations from Goldman Sachs ("Expected Dividends") and using the actual dividends that were paid out for each index ("Realized Dividends"). The sample period is January 2007 through December 2017.

	Futures Market Returns				Spot Market Returns			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Expected Dividends	-5.93*	-4.76**	-6.07*	-4.81**	-4.38	-3.09	-4.43	-3.01
	(-1.99)	(-2.89)	(-1.89)	(-2.83)	(-1.51)	(-1.61)	(-1.41)	(-1.49)
Realized Dividends	-4.57	-4.26**	-4.66	-4.35**	-3.17	-2.76	-3.21	-2.78
	(-1.34)	(-2.34)	(-1.29)	(-2.31)	(-0.97)	(-1.42)	(-0.93)	(-1.37)
Time FE	No	No	Yes	Yes	No	No	Yes	Yes
Entity FE	No	Yes	No	Yes	No	Yes	No	Yes

Table A.8: **LMH Liquidity Demand Strategy Returns: Realized Dividends vs. Ex-ante Expected Dividends, 2007-2017**

The table reproduces the LMH Liquidity Demand trading strategies series constructed using dividend expectations from Goldman Sachs ("Expected Dividends") and using the actual dividends that were paid out for each index ("Realized Dividends"). "XS" strategies are cross-sectional trading strategies and "TS" strategies are timing strategies. The sample period is January 2007 through December 2017. Strategies are weekly rebalanced.

			Weekly Mean	Annualized Mean	Annualized Standard Deviation	Skewness	Kurtosis	Annualized Sharpe Ratio
XS	Futures	Expected Dividends	0.13%	6.96%	7.60%	0.54	3.73	0.91
		Realized Dividends	0.12%	6.41%	7.72%	0.33	2.50	0.83
	Spot	Expected Dividends	0.10%	5.43%	7.34%	0.26	2.69	0.74
		Realized Dividends	0.09%	4.73%	7.50%	0.13	2.54	0.63
TS	Futures	Expected Dividends	0.31%	16.14%	23.06%	0.72	4.81	0.70
		Realized Dividends	0.26%	13.44%	23.16%	0.41	5.89	0.58
	Spot	Expected Dividends	0.26%	13.50%	22.67%	0.62	4.52	0.60
		Realized Dividends	0.20%	10.49%	22.75%	0.33	5.72	0.46

A.4 Index Level Regressions

As a supplement to the panel regressions we present to test the main predictions of the model, we present the results from time-series regressions for each index. As a test of the first prediction of the model, Figure A.3 plots t-statistics of contemporaneous regressions of the basis on net futures positioning of each investor category. As a test of prediction two of the model, Figure A.4 plots t-statistics of contemporaneous time-series regressions of weekly futures and spot market returns on changes in the basis for each index in our sample. As a test of prediction three of the model, Figure A.5 plots t-statistics of time-series regressions of weekly futures and spot market returns on the basis measured at the end of the previous week. For all index-level regressions, standard errors are calculated using the Newey-West adjustment with 12 lags to control for potential autocorrelations in errors. In each plot, we also report the t-statistics of the pooled time-series regression with entity fixed effects reported in the main specification.

Figure A.3: **Contemporaneous Relationship Between the Basis and Dealer Futures Positions**

The figure plots the t-statistics from contemporaneous time-series regressions of the basis on net futures positions for each American index in our sample. Standard errors are calculated using a Newey-West correction with twelve lags. The pooled bars corresponds with t-statistics reported in Table 3 for the panel regressions with entity fixed effects.

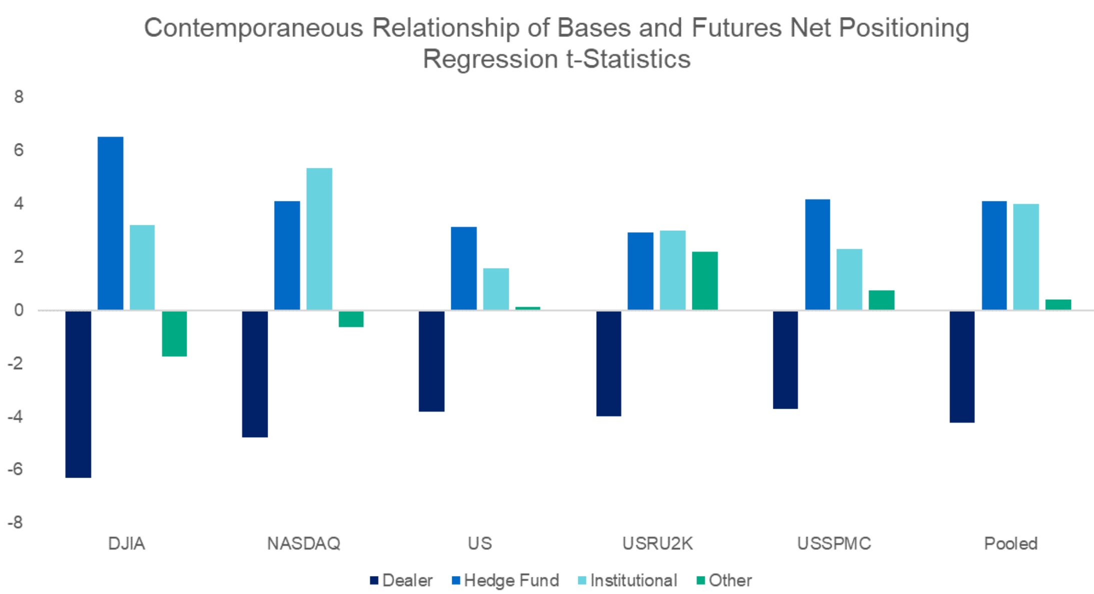


Figure A.4: **Contemporaneous Relationship Between Changes in the Basis and Returns**

The figure plots the t-statistics from contemporaneous time-series regressions of weekly futures and spot market returns on changes in the basis for each index in our sample. Standard errors are calculated using a Newey-West correction with twelve lags. The pooled bars correspond with t-statistics reported in Table 4 for the panel regressions with entity fixed effects.

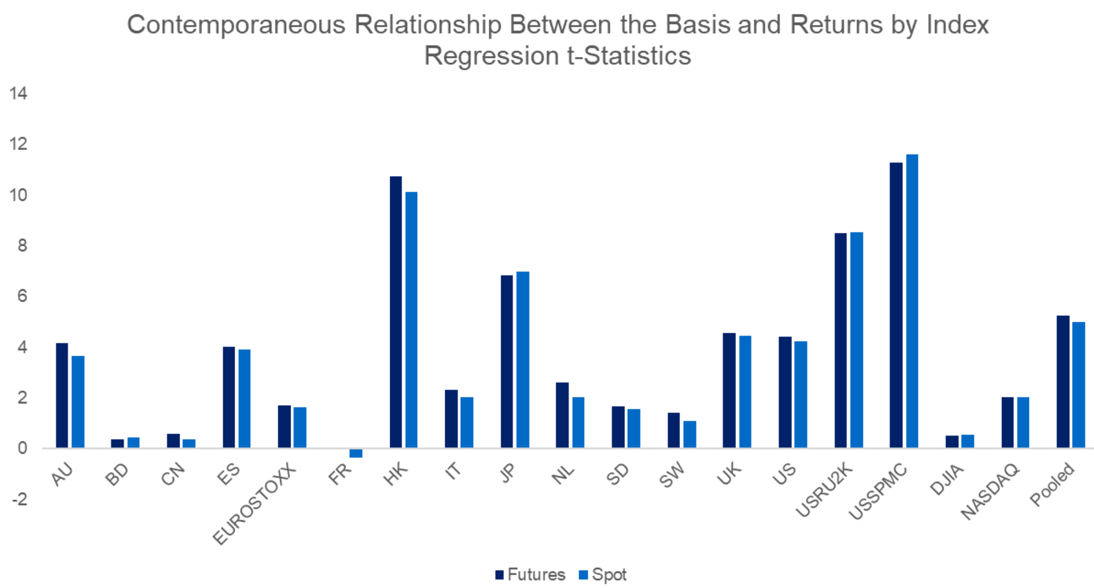
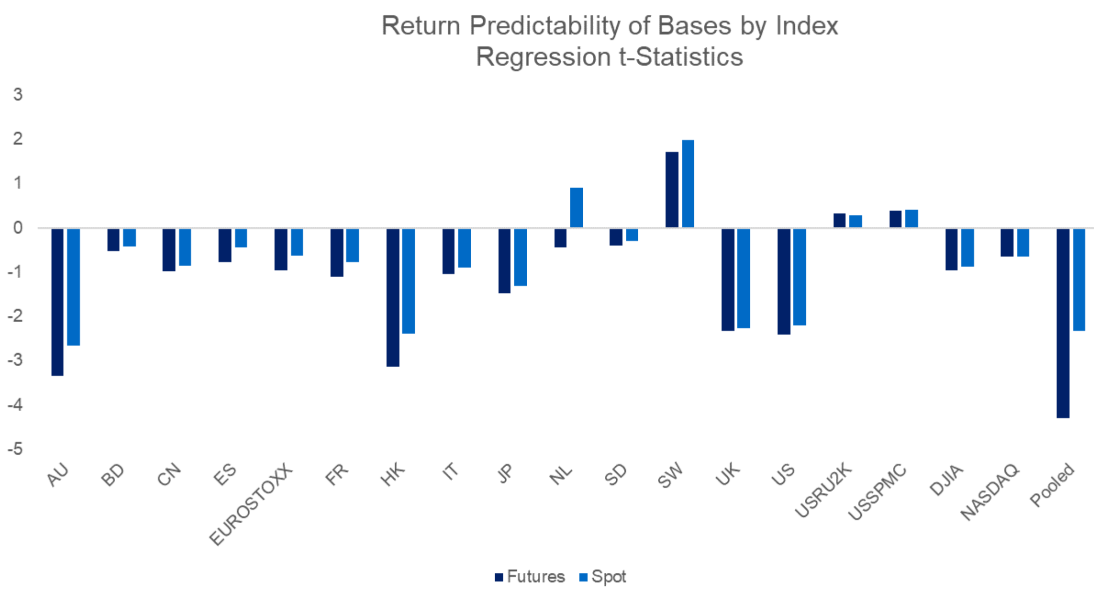


Figure A.5: **Return Predictability of the Basis**

The figure plots the t-statistics from predictive time-series regressions of weekly futures and spot market returns on the lagged for each index in our sample. Standard errors are calculated using a Newey-West correction with twelve lags. The pooled bars correspond with t-statistics reported in Table 5 for the panel regressions with entity fixed effects.



A.5 Impact of Assumed Benchmark Funding Rates

In our construction of the basis, we assume that the benchmark funding rate for an index is the interbank offer rate in the location that the index trades. In the literature on Covered Interest Rate (CIP) deviations, Rime et al. (2019) point out that interbank rates likely do not reflect the true funding rate at which arbitrageurs can fund positions. Calculating the profitability of CIP arbitrage requires accurately capturing the uncollateralized borrowing rates at which traders in currency markets can fund their positions. Rime et al. (2019) find that only a limited number of financial institutions are able to profit from CIP arbitrage.

Our main goal in this paper is not to analyze the profitability of the futures-spot arbitrage trade, but is rather to connect deviations from the law of one price, as measured using benchmark borrowing rates, with liquidity demand that simultaneously affects futures prices and spot prices. Nevertheless, the discussion in currency markets does raise the question as to how our results may be impacted by using interbank lending rates in our construction of the basis, which may not reflect the true uncollateralized rate at which arbitrageurs can borrow. To address this question, we run cross-sectional analyses of the basis in markets where the benchmark borrowing rates are the same. For example, if we compare bases for futures contracts on US indices, the cross-sectional dispersion in bases does not depend upon whether we assume the benchmark funding rate is LIBOR or the US Treasury bill rate because the benchmark rate used is the same for all of the US indices. Comparing bases across indices in the same market allows us to quantify the magnitude of bases without having to know the exact funding rate at which investors can finance their positions. Moreover, it also allows us to test if the patterns in returns that we document are affected by assumptions about benchmark borrowing rates.

First, the analysis in Section 3.1 pertains solely to indices traded on US exchanges. Hence, the regression results with time fixed effects in Table 3 of the basis on futures positioning remain the same, no matter what benchmark funding rate in the US is used. The evidence suggests that a one standard deviation difference in dealer futures positioning corresponds with a -10 (with time + entity fixed effects) to a -25.5 bp (with time fixed effects) difference in the basis across indices, no matter what benchmark rate (Overnight Indexed Swap rates, T-Bill rates, or Secured Overnight Financing Rates) is used, since these rates are the same for all U.S. indices and hence difference out in the cross-sectional strategy.

Second, we look to the cross-section of Eurozone equity indices in our sample - the EUROSTOXX Index, the German DAX Index, the French CAC40 Index, the Spanish IBEX 35 Index, the Italian FTSE MIB Index, and the Dutch AEX Index. We find that the median cross-sectional standard deviation of the basis across Eurozone indices is 39 basis points over our sample. The median cross-sectional standard deviation is 29 basis points post-2010. Hence, even controlling for the benchmark interest rate, there is evidence of heterogeneity in bases across indices. To understand whether differences in the basis capture the same types of liquidity effects within the Eurozone, we construct a within Eurozone cross-sectional LMH Liquidity strategy, following Equation (18). The weekly rebalanced strategy has a Sharpe ratio of 0.53 (t-statistic of 2.19) when implemented in futures markets, and a Sharpe ratio of 0.37 (t-statistic of 1.57) when implemented in the spot market. The monthly rebalanced strategy has a Sharpe ratio of 0.71 in futures markets (t-statistic of 2.93) and a Sharpe ratio of 0.61 when implemented in the spot market (t-statistic of 2.53). The futures and spot market predictability of the basis persist even when looking within Europe, where there are no differences in benchmark borrowing rates, and the equity indices have highly correlated returns.[21] This evidence suggests that differences in assumed benchmark borrowing rates are unlikely to explain our results.

[21] We could perform a similar analysis for the return predictability of bases in the cross-section of US indices. However, this is less informative, as it yields a largely static portfolio that is long small cap stocks and short large cap stocks, due to the strong negative basis of the Russell 2000.

A.6 Global Equities: Basis Return Predictability and US Indices

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

We first repeat the full-sample regression in Panel A of Table 4 for the two additional cross-sections. The results are reported in Table A.9, alongside the regression results presented in the main text. We also repeat the full-sample regression in Panel A of Table 5 for the two additional cross-sections. Table A.10 reports the results from the regressions alongside the regression results from the main table. The regression results are all very similar across the three cross-sections.

We next form alternative LMH Liquidity demand portfolios using the two alternative cross-sections, in addition to our baseline specification. Table A.11 displays the statistics of the returns of the strategies. There is a slight decay in the performance of the cross-sectional strategies without the US indices, and a slight improvement in the performance of the timing strategies, but the differences are very small.

Table A.9: **Contemporaneous Relationship Between the Basis and Returns, with Different Indices**

The table reproduces the regressions in Panel A of Table 4, using different cross-sections of assets. The row labeled "S&P500" excludes all US indices except for the S&P500 index. The row labeled "Ex US" excludes all US indices.

	Futures Market Returns				Spot Market Returns			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Main Specification	0.44***	0.44***	0.17***	0.17***	0.41***	0.41***	0.13***	0.13***
	(5.25)	(5.25)	(5.39)	(5.39)	(4.99)	(4.99)	(3.91)	(3.91)
S&P500	0.40***	0.40***	0.15***	0.15***	0.36***	0.36***	0.11***	0.11***
	(6.07)	(6.07)	(4.92)	(4.92)	(5.83)	(5.83)	(3.30)	(3.30)
Ex US	0.39***	0.39***	0.15***	0.15***	0.35***	0.35***	0.11***	0.11***
	(6.15)	(6.15)	(4.79)	(4.79)	(5.89)	(5.89)	(3.20)	(3.20)
Time FE	No	No	Yes	Yes	No	No	Yes	Yes
Entity FE	No	Yes	No	Yes	No	Yes	No	Yes

t statistics in parentheses

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

Table A.10: **Global Equities Basis Return Predictability, with Different Indices**

The table reproduces the regressions in Panel A of Table 5, using different cross-sections of assets. The row labeled "S&P500" excludes all US indices except for the S&P500 index. The row labeled "Ex US" excludes all US indices.

	Futures Market Returns				Spot Market Returns			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Main Specification	-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)
S&P500	-5.29***	-4.01***	-5.35***	-3.95***	-3.64**	-2.38**	-3.65**	-2.28**
	(-3.92)	(-4.53)	(-3.88)	(-4.58)	(-2.80)	(-2.37)	(-2.76)	(-2.29)
Ex US	-5.14***	-4.00***	-5.19***	-3.94***	-3.49**	-2.39**	-3.50**	-2.28**
	(-3.86)	(-4.46)	(-3.84)	(-4.50)	(-2.72)	(-2.34)	(-2.69)	(-2.25)
Time FE	No	Yes	No	Yes	No	Yes	No	Yes
Entity FE	No	No	Yes	Yes	No	No	Yes	Yes

t statistics in parentheses

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

Table A.11: **LMH Liquidity Demand Strategy Returns: Impact of US Indices**

The table reproduces the LMH Liquidity Demand trading strategies series constructed using different a different set of indices. Strategies labeled "S&P500" exclude US indices except for the S&P500. Strategies labeled "Ex US" exclude all indices. "XS" strategies are cross-sectional strategies and "TS" strategies are timing strategies. Strategies are weekly rebalanced.

			Weekly Mean	Annualized Mean	Annualized Standard Deviation	Skewness	Kurtosis	Annualized Sharpe Ratio
XS	Futures	Baseline	0.14%	7.27%	8.40%	0.52	3.99	0.86
		S&P500	0.14%	7.31%	8.81%	0.25	3.18	0.83
		Ex US	0.14%	7.14%	9.17%	0.19	2.79	0.78
	Spot	Baseline	0.10%	5.27%	8.37%	0.17	3.70	0.63
		S&P500	0.10%	5.33%	8.69%	0.07	2.86	0.61
		Ex US	0.10%	5.09%	9.03%	0.02	2.40	0.56
TS	Futures	Baseline	0.28%	14.61%	21.53%	0.52	4.09	0.68
		S&P500	0.31%	16.21%	22.64%	0.61	3.20	0.72
		Ex US	0.32%	16.44%	22.96%	0.61	3.13	0.72
	Spot	Baseline	0.22%	11.28%	21.27%	0.36	3.87	0.53
		S&P500	0.24%	12.62%	22.19%	0.54	2.95	0.57
		Ex US	0.25%	12.84%	22.47%	0.55	2.88	0.57

A.7 Implications for Implied Interest Rates from Derivatives

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

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

With these caveats in mind, we recast our results in terms of understanding interest rates embedded in futures prices. First, consider the results relating the basis to futures positioning from Table 3, which provide some quantitative guidance on how much futures demand can affect futures-implied interest rates. We find that a one standard deviation increase in the futures positions of dealers corresponds with a 10 basis point decrease in the basis, which equivalently corresponds to a 10 basis point decrease in the implied interest rate in futures. Taking the estimates from Binsbergen et al. (2019), who compare option-implied interest rates to matched-maturity Treasury yields, our results suggest that maybe 10 to 20 bps may be coming from demand shocks (depending on their size). These effects are small, but not inconsequential. The results also suggest that when interpreting the behavior of derivatives-implied interest rates in event-study contexts, it might be important to understand how those events impact leverage demand for risky assets.

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

Second, the demand channel can also explain some of the cross-sectional heterogeneity in bases we observe within a given market. For example, the large variation in bases across U.S. equity indices in Table A.1 is difficult to justify purely from differences in marginal investor funding rates, but may be accommodated by a combination of varying leverage demand and intermediary costs. Consider the basis in Russell 2000 futures, which provides an interesting, albeit extreme, case. Table A.1 shows that the basis for Russell 2000 futures is, on average, -76 basis points, suggesting that the interest rate embedded in its futures are consistently far lower than interbank lending rates. The futures positioning and securities lending data for the Russell 2000 suggest potential reasons for this large negative basis. Russell 2000 stocks, which are small-cap, are difficult to borrow and have high security lending fees (on average 64 bps, which is the highest among the equity indices in our sample). Hedge funds engaged in small-cap equity strategies might have persistent demand for short positions in R2000 futures, if they are a more convenient/cheaper vehicle to hedge their long positions than short-selling individual names. This demand for short futures exposure would result in a negative futures-spot basis. Another story consistent with these observations is that high security lending fees make it particularly cheap for dealers to provide long leverage in futures on the R2000, which also results in a negative basis. In both cases, R2000 futures illustrate an example where leverage demand and dealer provision of leverage can substantially change the interest rates embedded in risky assets.

Finally, we directly back out the interest rates implied by S&P 500 futures prices to compare them to Binsbergen et al. (2019). We construct 3-month implied interest rates for S&P500 futures by linearly interpolating the interest rates embedded in the nearest and second-nearest to expiration futures contracts.[23] We construct the Treasury basis as the 3-month futures implied interest rate minus the 3-month US Treasury yield. We similarly construct the 3-month LIBOR basis as the 3-month futures implied interest rate minus 3-month LIBOR. The first column of Panel A Table A.12 reports the average values for the futures implied interest rates and bases that we construct, as well as the values for the corresponding 3-month benchmark interest rates. We also report the same statistics for 6- and 12-month SPX box-spread implied interest rates, obtained from Jules van Binsbergen's website.

Table A.13 reports the correlations between the LIBOR bases, Treasury bases, and the posi-

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

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

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

Table A.12: **S&P 500 Derivatives Implied Interest Rates**

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

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

Table A.13: **S&P 500 Interest Rate Spread Correlations**

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

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

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

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

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

A.8 Markit Securities Finance Data Coverage

Table A.14: **Markit Securities Finance Data Coverage Across Indices**

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

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