Internet Appendix for
"Beyond Basis Basics: Liquidity Demand and Deviations from the Law of One Price"

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Contents

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[1]Citation format: Hazelkorn, Todd M., Tobias J. Moskowitz, and Kaushik Vasudevan, Internet Appendix for "Beyond Basis Basics: Liquidity Demand and Deviations from the Law of One Price," *Journal of Finance* [DOI String]. Please note: Wiley-Blackwell is not responsible for the content or functionality of any additional information provided by the authors. Any queries (other than missing material) should be directed to the authors of the article.

IA.A. The Futures-Cash Basis Across Indices

IA.A.1. Summary Statistics

Table IA.I. 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 IA.II. 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

IA.A.2. Futures-Cash Bases Dynamics

Figure IA.1 plots the five-day rolling average of the futures-cash basis for each index in the sample. The figure reveals a few interesting observations.

First, there are substantial differences in the time-series variation of the futures-cash basis across indices (this can also be observed in Table IA.II). The basis in the Hong Kong Hangseng Index, in particular, is the most volatile, while the basis is considerably less volatile for the DJIA and S&P 500 indices.

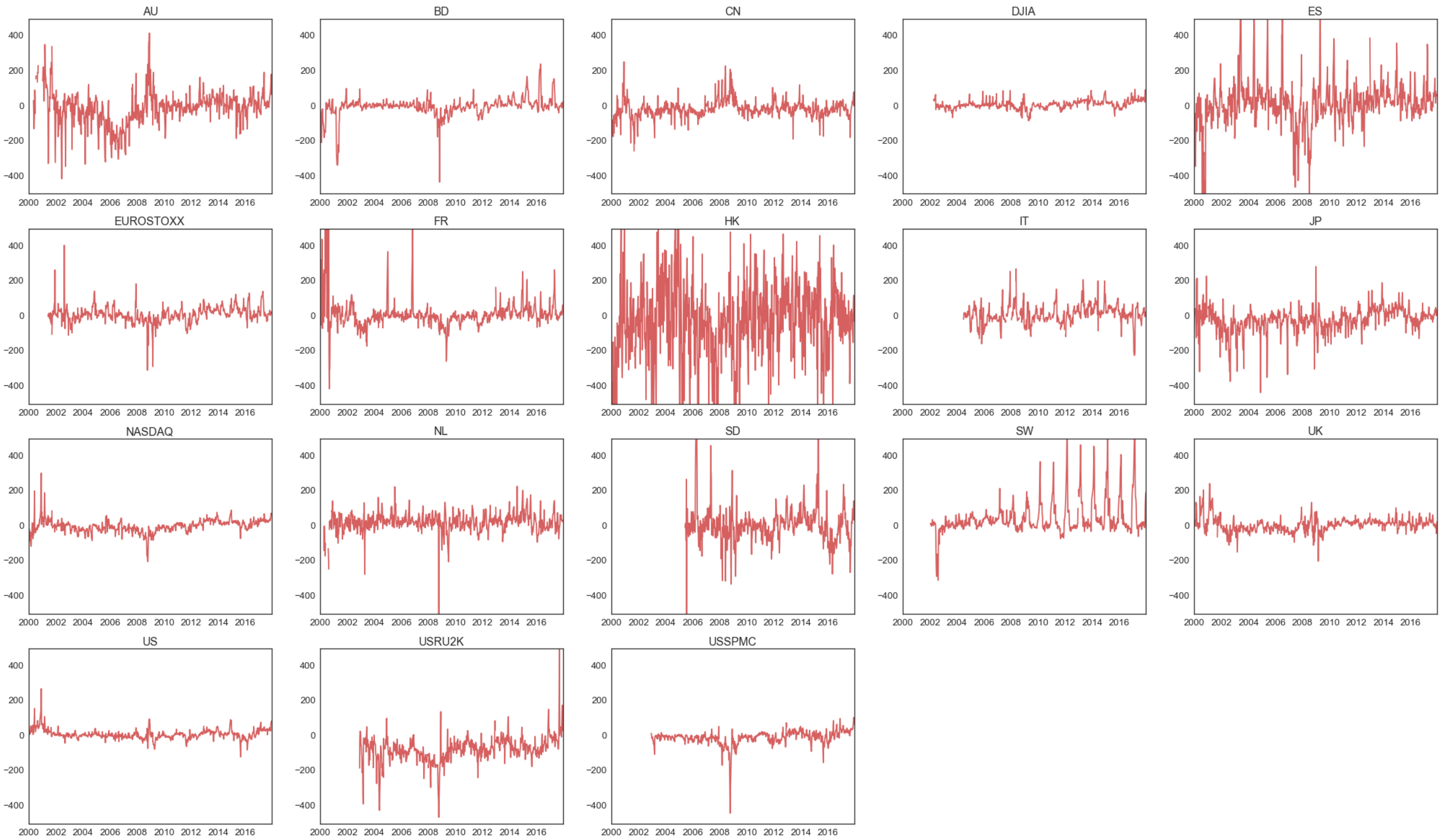
Second, there are some periodic spikes in the basis that we measure for each of the indices in the sample, corresponding with futures expiration dates. These spikes arise from a combination of scaling by maturity for contracts that are close to maturity, as well as temporary price dislocations that occur in the nearest-maturity contracts when market activity 'rolls' to the second-nearest maturity contract.

Third, some indices (for example, the German DAX Index and the Swiss SMI index) also appear to have seasonal spikes in the basis. These spikes tend to coincide with dividend season for the stocks in these indices. These spikes are likely not driven by mismeasurement of dividends; the German DAX index is a total return index where dividends do not enter into futures contract prices, but nevertheless still exhibits these seasonal patterns. Speculatively, these patterns may be related to tax-related trading around dividend ex-dates.

Fourth, we observe particularly large bases during the GFC for most of the indices in the sample, and in particular, in October 2008. Of course, this is to be expected, and is consistent with a similar increase in the magnitude of arbitrage spreads across different asset markets during this period.

Figure IA.1. Futures-Cash Bases Across Indices

The figure plots the five-day rolling average of the futures-cash basis for each index in the sample.



IA.B. 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 (8) 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 IA.B.1 provides evidence that dividends are generally announced one to three months in advance of dividend ex-date. Internet Appendix IA.B.2 plots monthly observations of dividend expectations versus the realized dividends, and shows that the two are very closely related. Internet Appendix IA.B.3 analyzes measurement error in the basis from our assumptions about dividends using two case studies, the first analyzing dividend futures prices in the United States, and the second comparing the basis of the DAX index, which is a total return index (where there is no issue associated with dividend measurement) and with the basis of the EUROSTOXX. In Internet Appendix IA.B.5, 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.

IA.B.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 IA.2 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 IA.2. 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.

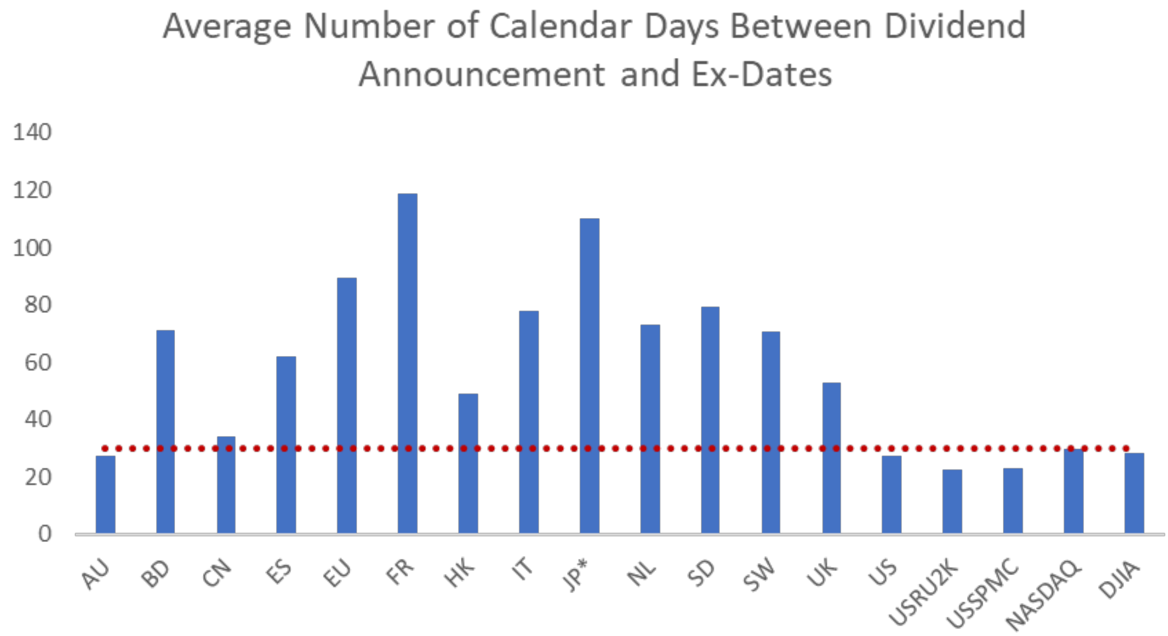
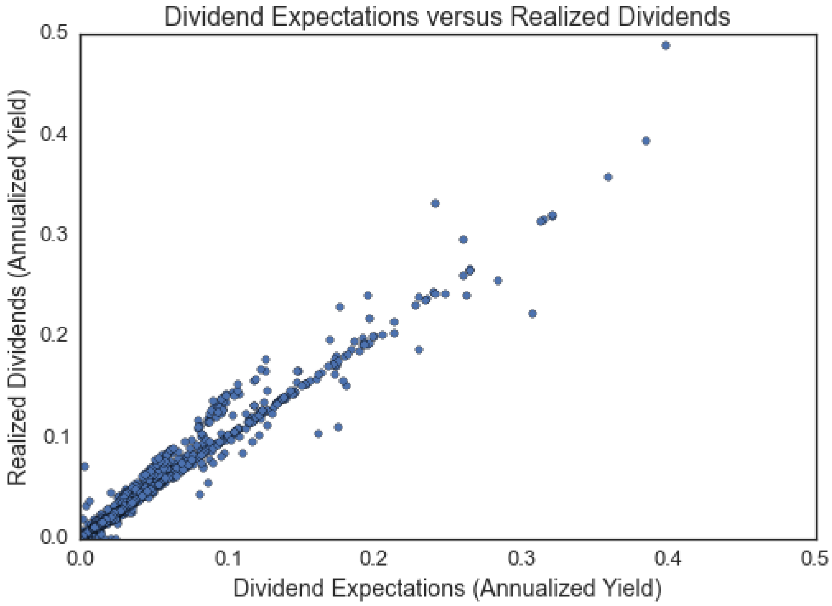


Figure IA.3. Dividend Expectations Versus Realizations



IA.B.2. Realized Dividends and Dividend Expectations

In Figure IA.3, we plot monthly observations of the GS dividend expectations used in the futures-cash basis calculation (expressed in annualized yield terms) versus monthly observations of the realized dividends, from Bloomberg (in annualized yield terms).[2] Dividend yields are calculated on a contract-by-contract basis. As in the construction of the basis, the dividend yields here correspond with the nearest maturity contract when it is more than 10 days from expiring, and subsequently correspond with a linear combination of the nearest- and second-nearest maturity contracts, with weight linearly transferring to the second contract. The sample period is from January 2007 through December 2017. Expectations are 0.99 correlated with realizations, and the R^2 of dividend expectations for explaining dividend realizations is 0.97, when asserting a zero intercept and a slope of 1.

[2]The very large dividend yields here come from the fact that companies in a number of countries in our sample pay dividends once annually, with the timing of ex-dividends highly clustered within an index.

IA.B.3. 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 (8).[3] In Figure IA.4, 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 IA.II, 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.

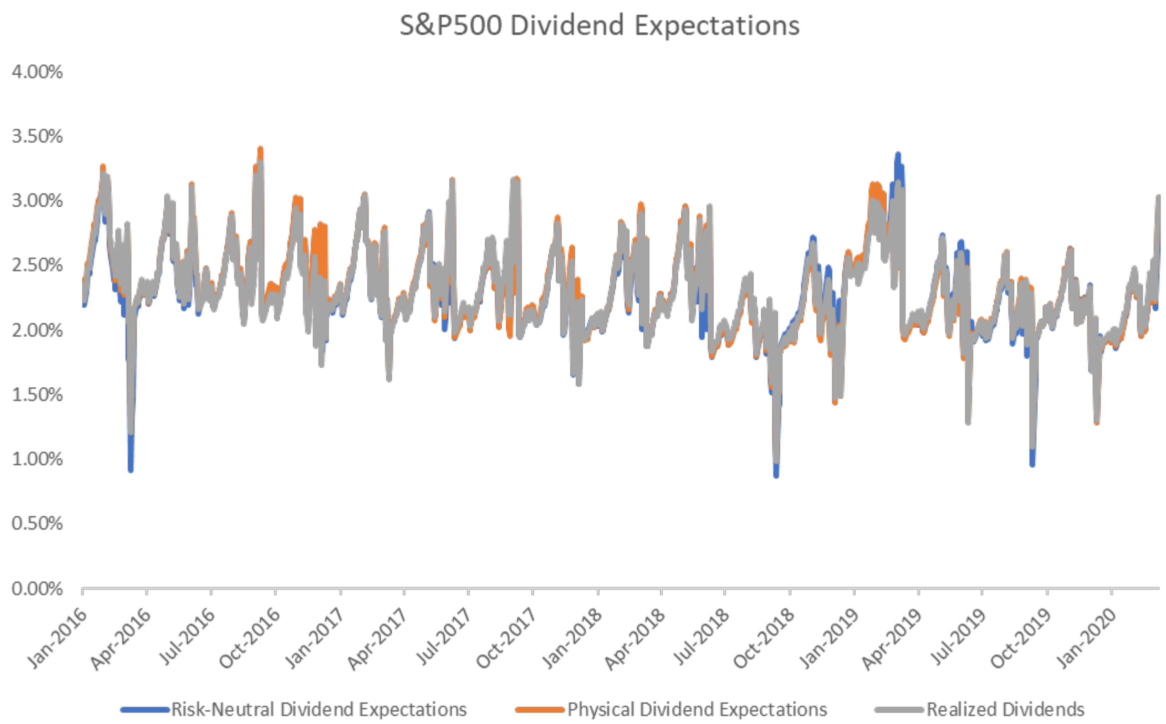
Second, our sample contains the German DAX index, which is unique in that it is a total

[3] 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.

return index. The level of the index is constructed by assuming that all dividends are reinvested, so issues with dividend mismeasurement are mitigated. Looking to the asset-by-asset summary statistics for the basis presented in Table IA.II, 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 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 IA.4. 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.



IA.B.4. 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 IA.B.3 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-cash 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-cash 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 IV 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 IA.III. 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 V using our basis series constructed under the various dividend risk premia estimates. Table IA.IV 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-cash basis series. Table IA.V 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-cash basis are not largely affected by assumptions about dividend risk premia.

Table IA.III. Contemporaneous Relationship Between the Basis and Returns under Dividend Risk Premia Assumptions

The table reproduces the regressions in Panel A of Table IV, using futures-cash 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	47.41***	17.95***	47.41***	17.95***	43.20***	13.68***	43.20***	13.68***
	(5.25)	(5.39)	(5.25)	(5.39)	(4.99)	(3.91)	(4.99)	(3.91)
20	48.56***	19.21***	48.59***	19.20***	44.53***	14.99***	44.56***	14.99***
	(4.80)	(6.51)	(4.80)	(6.51)	(4.64)	(4.69)	(4.64)	(4.69)
50	49.04***	19.57***	49.07***	19.56***	45.05***	15.39***	45.08***	15.39***
	(4.69)	(6.50)	(4.69)	(6.50)	(4.53)	(4.80)	(4.53)	(4.81)
80	49.17***	19.78***	49.20***	19.78***	45.25***	15.68***	45.28***	15.68***
	(4.66)	(6.45)	(4.66)	(6.44)	(4.50)	(4.86)	(4.50)	(4.86)
110	48.97***	19.86***	49.00***	19.85***	45.15***	15.86***	45.17***	15.86***
	(4.70)	(6.40)	(4.70)	(6.39)	(4.53)	(4.88)	(4.53)	(4.88)
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 IA.IV. Global Equities Basis Return Predictability Under Dividend Risk Premia Assumptions

The table reproduces the regressions in Panel A of Table V, using futures-cash 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 IA.V. Global Equity LMH Liquidity 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 Spot 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 Spot 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

IA.B.5. 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 IV for the sub-sample from 2007-2017 using the dividend expectations from Goldman Sachs and using realized index dividends. Table IA.VI 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 V, 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 IA.VIII). Once again, this is consistent with a slight understatement of the strategy's profitability when using realized as opposed to expected dividends.

Table IA.VI. Contemporaneous Relationship Between Changes in the Basis and Returns, 2007-2017

The table reproduces the regressions in Panel A of Table IV using futures-cash 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	79.00***	27.25***	79.00***	27.26***	74.00***	21.92***	74.01***	21.92***
	(4.01)	(4.81)	(4.01)	(4.81)	(3.91)	(3.66)	(3.92)	(3.66)
Realized Dividends	75.47***	27.05***	75.48***	27.05***	70.65***	22.02***	70.65***	22.02***
	(4.19)	(4.68)	(4.19)	(4.68)	(4.08)	(3.57)	(4.08)	(3.57)
Time FE	No	Yes	No	Yes	No	Yes	No	Yes
Entity FE	No	No	Yes	Yes	No	No	Yes	Yes

Table IA.VII. Global Equities Basis Return Predictability, 2007-2017

The table reproduces the regressions in Panel A of Table V using futures-cash 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 IA.VIII. 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

IA.C. 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 IA.5 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 IA.6 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 IA.7 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 IA.5. 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 III for the panel regressions with entity fixed effects.

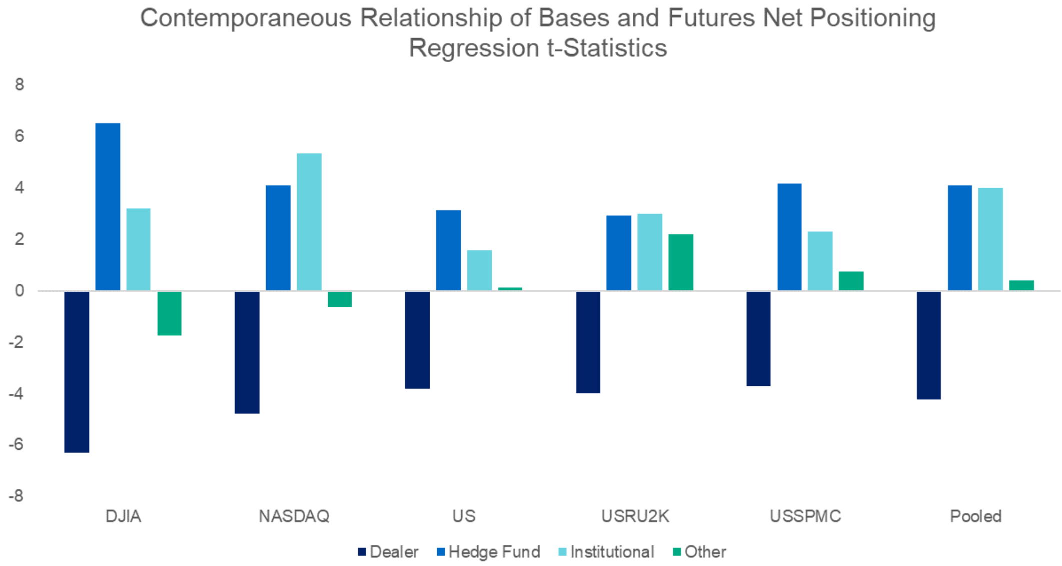


Figure IA.6. Contemporaneous Relationship Between Changes in the Basis and Returns

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 IV for the panel regressions with entity fixed effects.

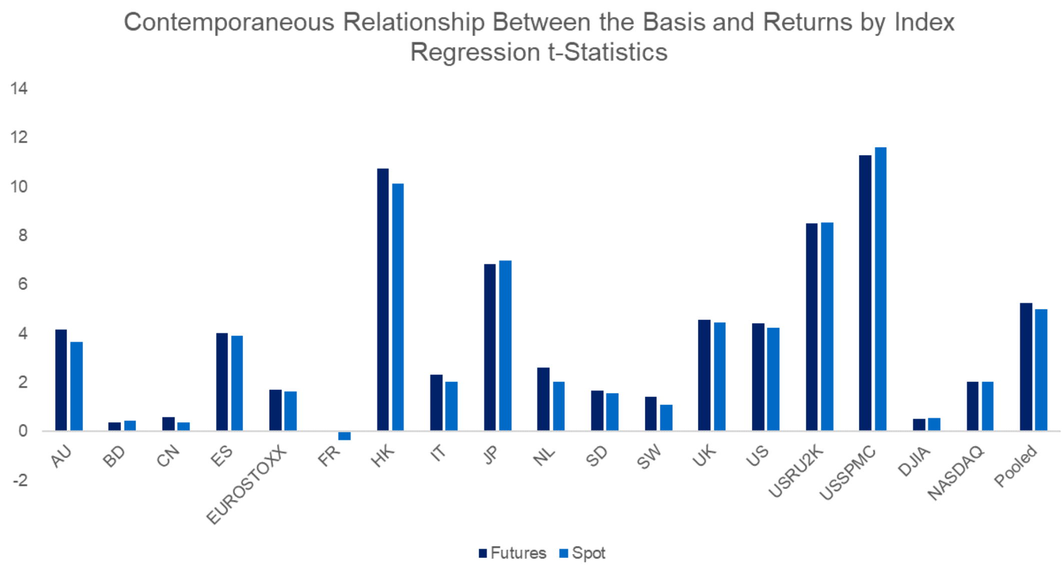
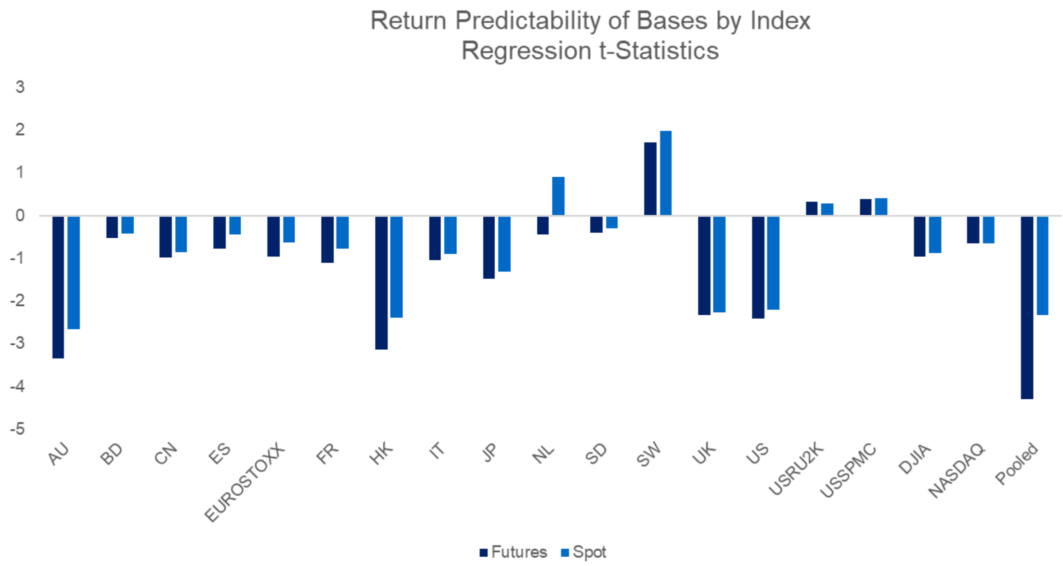


Figure IA.7. Return Predictability of the Basis

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 V for the panel regressions with entity fixed effects.



IA.D. 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 A pertains solely to indices traded on US exchanges. Hence, the regression results with time fixed effects in Table III 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.[4] This evidence suggests that differences in assumed benchmark borrowing rates are unlikely to explain our results.

[4]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.

IA.E. 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 IV for the two additional cross-sections. The results are reported in Table IA.IX, alongside the regression results presented in the main text. We also repeat the full-sample regression in Panel A of Table V for the two additional cross-sections. Table IA.X 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 IA.XI 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 IA.IX. Contemporaneous Relationship Between the Basis and Returns, with Different Indices

The table reproduces the regressions in Panel A of Table IV, 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	47.41***	17.95***	47.41***	17.95***	43.20***	13.68***	43.20***	13.68***
	(5.25)	(5.25)	(5.39)	(5.39)	(4.99)	(4.99)	(3.91)	(3.91)
S&P500	42.47***	16.34***	42.46***	16.34***	38.14***	12.14***	38.14***	12.14***
	(6.07)	(4.92)	(6.07)	(4.92)	(5.83)	(3.30)	(5.83)	(3.30)
Ex US	41.83***	16.11***	41.83***	16.11***	37.53***	11.92***	37.53***	11.92***
	(6.15)	(4.79)	(6.15)	(4.79)	(5.89)	(3.20)	(5.89)	(3.20)
Time FE	No	Yes	No	Yes	No	Yes	No	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 IA.X. Global Equities Basis Return Predictability, with Different Indices

The table reproduces the regressions in Panel A of Table V, 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 IA.XI. 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

IA.F. 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. (2021) 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. (2021) extract interest rates from, so it is interesting to examine our results through this complementary lens.

The futures-cash 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. (2021) 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 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.[5]

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 III, which provide some quantitative guidance on how much futures demand can

[5] In equilibrium, the supply of, and demand for, leverage can be related to the convenience yield (e.g., in the model of Diamond (2020)). The futures demand we study could very well be related to the Treasury convenience yield, but this potential relationship is outside the scope of our paper.

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. (2021), 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 demand for risky assets.

Second, the demand channel can also explain some of the cross-sectional heterogeneity in bases we observe within a given market. For example, the large variation in bases across U.S. equity indices in Table IA.II is difficult to justify purely from differences in marginal investor funding rates, but may be accommodated by a combination of varying futures demand and intermediary costs. Consider the basis in Russell 2000 futures, which provides an interesting, albeit extreme, case. Table IA.II 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-cash 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 futures 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. (2021). 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.[6] 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 IA.XII 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 IA.XIII reports the correlations between the LIBOR bases, Treasury bases, and the positions of dealers in S&P 500 futures contracts. Panel A reports correlations from June 2006 to December 2017 and Panel B reports correlations from January 2010 to December 2017. The 3-month LIBOR basis we estimate from futures contracts is 0.52 and 0.37 correlated with the 6- and 12-month LIBOR bases constructed using the vBDG box spreads in the longer sample (and 0.54 and 0.51 in the post-2010 sample). The 3-month Treasury basis we estimate from futures contracts is 0.81 and 0.80 correlated with the Treasury bases constructed using vBDG box spreads in the longer sample (and 0.44 and 0.41 correlated in the post-2010 sample). These numbers suggest commonality in the futures basis we estimate and the bases implied by the vBDG box spreads. The 3-month LIBOR and Treasury bases that we estimate are negatively correlated with dealers' futures positions (correlations of -0.25 and -0.55 for the

[6]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

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 et al. (2021); 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 IA.XII. 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. (2021) (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 IA.XIII. 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. (2021). 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

IA.G. Studying the Properties of the Trading Strategies

We return to the LMH trading strategies and more closely study their properties. We study the trading strategies' relationship with other known return factors for equity indices, whether cross-sectional or time-series variation is more important for the strategies' returns, the holding period returns of the strategies, and the relationship between the strategies' returns and funding conditions.

IA.G.1. Spanning Tests and Factor Exposures

Table IA.XIV reports regression results of the LMH strategy returns on 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, 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 indicate that the LMH strategy returns are not explained by exposure to other well-known factors in global equity indices. Notably, the evidence also suggests the LMH strategies capture a distinct dimension of liquidity provision from reversal strategies. Additionally, the LMH timing strategies are strongly negatively correlated with time-series momentum. This 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. For equity indices, we show that dealers are primarily on the other side of hedge fund trading. The results suggest 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, consistent with liquidity providers earning compensation for absorbing demand.

IA.G.2. What Variation Matters for Return Predictability?

We next decompose the LMH strategies to better understand what variation in bases is important for explaining the strategy returns.

We first study whether the LMH time-series strategies' returns come from capturing common time-series variation in the basis across indices, or if index-specific time-variation in the basis is the primary driver. We decompose the LMH time-series portfolio into a *basket timing* portfolio, which takes an equal weight in each index equal to the average weight of all securities in that period in the LMH time-series portfolio, $\bar{w}_t = \frac{1}{N}\sum_{i=1}^{N} w_t^i$; and an *idiosyncratic* *timing* portfolio, in which the weight of asset i is equal to the difference of asset i's weight in the LMH portfolio and the basket timing portfolio, $w^i_{t,\text{idiosyncratic}} = w^i_t - \bar{w}_t$. The basket timing portfolio captures the strategy returns related to common time-series variation in the basis across indices, while the idiosyncratic timing portfolio captures the strategy returns coming from index-specific time-variation in the basis.

Panel A of Table IA.XV reports statistics on the returns of the basket timing and idiosyncratic timing portfolios. The average annualized return of the idiosyncratic timing portfolio is 9.95% in futures markets and 6.90% in spot markets, corresponding with annualized Sharpe ratios of 0.83 and 0.59. The averaged annualized return of the basket timing portfolio is 5.15% in futures markets and 4.75% in spot markets, corresponding with annualized Sharpe ratios of 0.28 and 0.26. The basket timing portfolio is more volatile (approximately 19% annualized) than the index timing portfolio (approximately 12% annualized), indicating that common time-series variation in returns across indices accounts for a more substantial share of variation in the timing portfolio's returns. Despite its lower share of variation in LMH strategy returns, the idiosyncratic timing portfolio accounts for more than half of the LMH strategy's returns, indicating that index-specific time-series variation in the basis plays an especially important role for explaining the return predictability of the basis.

We also study the LMH cross-sectional strategy to understand if cross-sectional return predictability of the basis comes from capturing static differences in the basis (and returns) across indices, or if time-varying differences in the basis across indices play a role. To do so, we decompose the cross-sectional trading strategy into a *static* portfolio and a *dynamic* portfolio. The weight of asset i in the static portfolio in each period is equal to the average weight of asset i in the LMH portfolio over the full sample, $\bar{w}^i \equiv \frac{1}{T}\sum_{t=1}^{T} w^i_t$. The weight of asset i in the dynamic portfolio at time t is equal to the difference between its weight in the LMH portfolio and the static portfolio, $w^i_{t,\text{dynamic}} = w^i_t - \bar{w}^i$.

Panel B of Table IA.XV reports statistics on the returns of the static and dynamic portfolios.

The average annualized return of the dynamic portfolio is 6.1% in the futures market and 4.2% in the spot market, corresponding with annualized Sharpe ratios of 0.77 and 0.53. The average annualized return of the static portfolio is 1.14% in the futures market and 1.04% in the spot market, corresponding with Sharpe ratios of 0.38 and 0.36. The results indicate that the lion's share of cross-sectional return predictability (upwards of 80%) comes from dynamic variation of the basis

The results from Table IA.XV indicate that cross-sectional variation in the basis plays an especially important role in explaining the return predictability of the basis. Moreover, return predictability doesn't just stem from indices that have more negative bases on average having higher returns in our sample. Rather, it stems from indices having higher returns *precisely when* their bases are more negative, suggesting that bases capture dynamic information about market returns.

IA.G.3. Holding Period Returns

In Figure IA.8, we plot the returns of the LMH Liquidity Demand strategies with different rebalance frequencies: weekly and monthly rebalancing (as reported in Table VI), as well as quarterly, semi-annual, and annual rebalancing. The figure reveals that the majority of the trading strategy returns are captured with a one-month holding period. For holding periods of one quarter or longer, the Sharpe ratio of the cross-sectional strategies is around 0.2, and is lower for the time-series strategies. The decay of the strategies' returns for longer holding periods is faster, for example, than time-series momentum strategies in equity index futures (Moskowitz et al. (2012)), where holding period returns remain almost equally as strong at the quarterly as the month frequency, and remain significant for holding periods of up to 12 months.

To better understand the holding period returns, in Internet Appendix IA.10, we analyze the returns of the LMH trading strategies formed using lagged values of the basis. For the cross-sectional strategy, strategy returns are similarly strong for lags of up to two weeks. The strategy performance substantially decays for longer lags, though returns remain modestly positive, consistent with the performance of the static portfolios. The time-series strategy returns decay more quickly, where most of the strategy performance is concentrated in lags of less than two weeks.

Another way to understand the holding-period returns of the strategies is by directly analyzing the persistence of the basis and dealer futures positions. The first plot in Figure IA.9 displays the daily autocorrelation function 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. The second plot in Figure IA.9 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. 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.[7] 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, which also supports our previous evidence.

IA.G.4. Aggregate Funding Conditions and LMH Trading Strategies

Here, we evaluate the relationship between the LMH trading strategies and aggregate funding conditions. The logic behind this analysis is that deteriorating funding conditions may

[7] For example, Hansch et al. (1998) and Hendershott and Menkveld (2014) report average half-lives of dealer inventory positions of two days or less on the London and New York Stock Exchanges.

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. Liquidity providers are traditionally assumed to be leveraged investors that may face funding constraints (for example, in Brunnermeier and Pedersen (2008)), which may suggest that the LMH trading strategies should perform poorly coincident with deteriorating funding conditions.[8] However, this effect may be muted by leveraged investors on the demand side that also face funding constraints, and reduce their futures positions when funding liquidity shocks hit.[9]

We run regressions of the LMH Liquidity Demand returns on variables related to aggregate funding conditions. These variables include 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). We also include 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 IA.XVI 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

[8] Drechsler et al. (2020) 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.

[9] For example, this is the story in Brunnermeier et al. (2008), who suggest that speculators executing the carry trade in currencies unwind their positions during deteriorating financial conditions.

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 investor behavior coincident 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,

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

$$\Delta F_t^{i,c} = \beta_{TED} \Delta TED_t \times \text{sign}(F_{t-1}^{i,c}) + \lambda_{TED} F_{t-1}^{i,c} + \eta_{i,TED} \tag{IA.2}$$

$$\Delta F_t^{i,c} = \beta_{HKM}(-HKM_t) \times \text{sign}(F_{t-1}^{i,c}) + \lambda_{HKM} F_{t-1}^{i,c} + \eta_{i,HKM} \tag{IA.3}$$

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 sign of the coefficients in the regression capture whether, in aggregate, investors in a particular category expand (positive sign) or contract (negative sign) their positions in response to shocks to funding conditions.

Table IA.XVII 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 do 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). 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. However, the effects are not strong enough that the LMH strategies 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.

Table IA.XIV. 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 IA.XV. Components of Basis Return Predictability

Panel A of the table reports statistics on the LMH time-series trading strategy, decomposed into two components: a 'basket timing' portfolio, which equally weights each index in each period using the average weight across all indices in the LMH timing portfolio in that period; and an idiosyncratic timing portfolio, where the weight of an index is equal to the difference between weight of the index in the LMH timing portfolio and the weight of the index in the basket timing portfolio. Panel B of the table reports statistics for the LMH cross-sectional trading strategy, decomposed into two components: a static portfolio, where the weight of an index in a given time is the average weight of the security in the LMH cross-sectional portfolio over the full sample; and a dynamic portfolio, where the weight of each index in each period is the difference between its weight in the LMH cross-sectional portfolio and the static portfolio.

Panel A: LMH Time-Series Strategies, Basket Timing versus Idiosyncratic Timing Performance

	Idiosyncratic Timing Returns				Basket Timing Returns			
	Weekly Mean	Annualized Mean	Annualized Volatility	Annualized Sharpe Ratio	Weekly Mean	Annualized Mean	Annualized Volatility	Annualized Sharpe Ratio
Futures Market	0.19%	9.95%	11.97%	0.83	0.10%	5.15%	18.63%	0.28
Spot Market	0.13%	6.90%	11.75%	0.59	0.09%	4.75%	18.53%	0.26

Panel B: Cross-Sectional Strategies, Static versus Dynamic Performance

	Dynamic Portfolio Returns				Static Portfolio Returns			
	Weekly Mean	Annualized Mean	Annualized Volatility	Annualized Sharpe Ratio	Weekly Mean	Annualized Mean	Annualized Volatility	Annualized Sharpe Ratio
Futures Market	0.12%	6.07%	7.85%	0.77	0.02%	1.14%	3.02%	0.38
Spot Market	0.08%	4.18%	7.84%	0.53	0.02%	1.04%	2.90%	0.36

Table IA.XVI. 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 IA.XVII. 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.

	$\Delta F_t^{\text{Dealer}}$			$\Delta F_t^{\text{Hedge Fund}}$			$\Delta F_t^{\text{Institutional}}$			$\Delta F_t^{\text{Other}}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\Delta VIX_t \times \text{sign}(F_{t-1})$	-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

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

Figure IA.8. Holding Period Returns of the Basis

The figure displays the annualized Sharpe ratios of the LMH Liquidity Demand strategy returns with different rebalance frequencies: weekly and monthly (as reported in Table VI), as well as quarterly, semi-annually, and annually. The Sharpe ratios of the cross-sectional strategies are plotted in blue, and the Sharpe ratios of the time-series strategies are plotted in red.

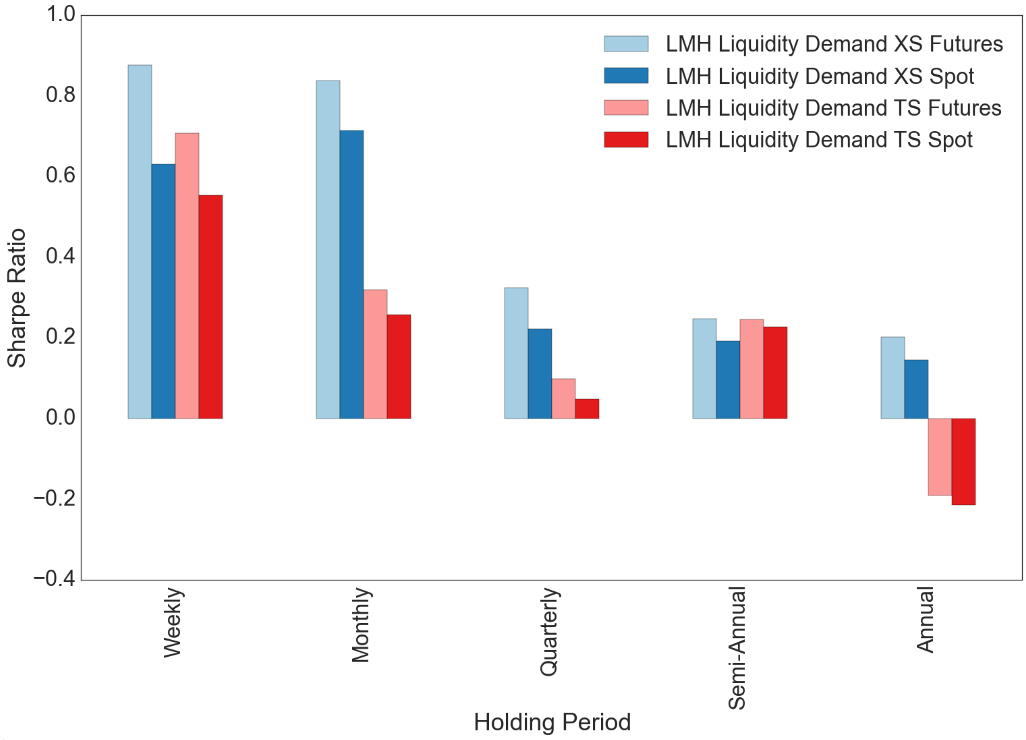


Figure IA.9. Autocorrelations of the Basis and Dealer Positions

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.

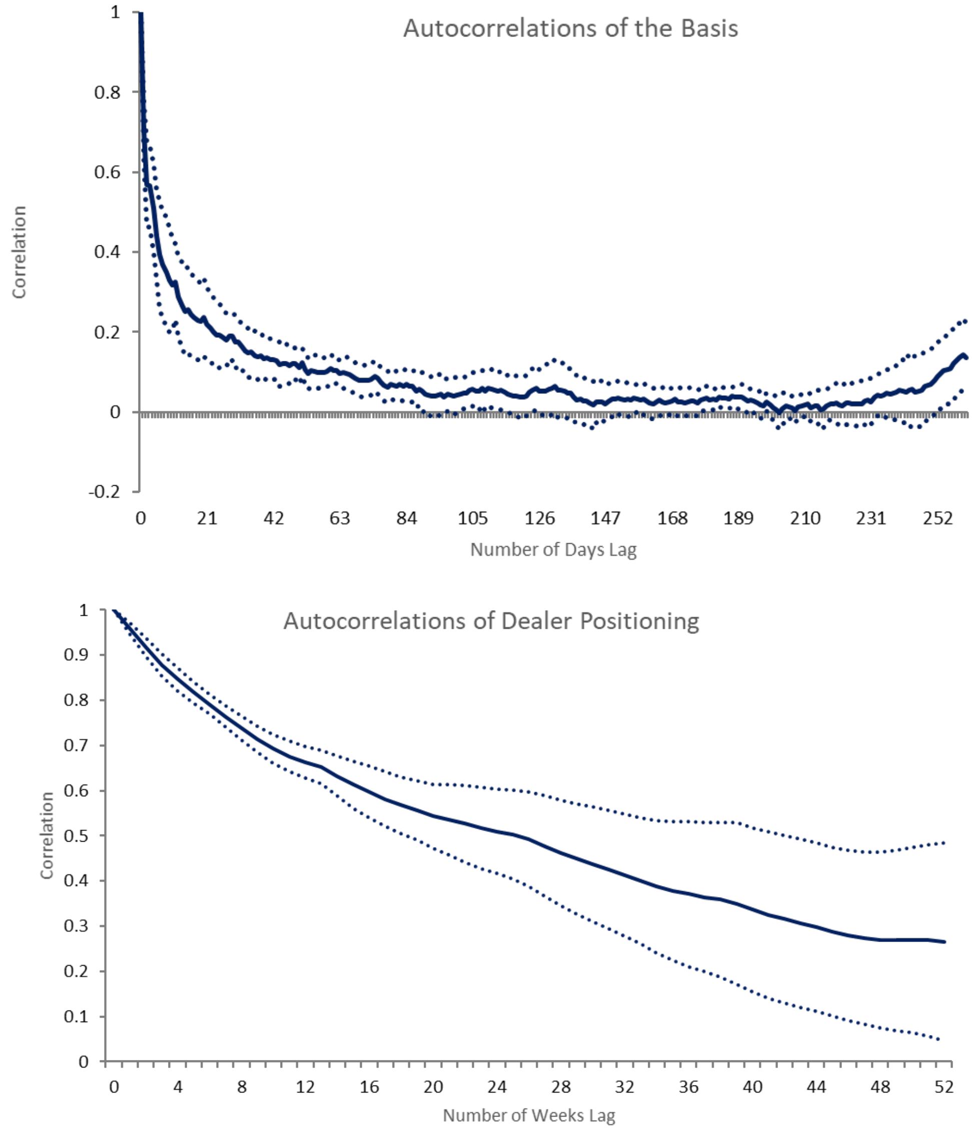
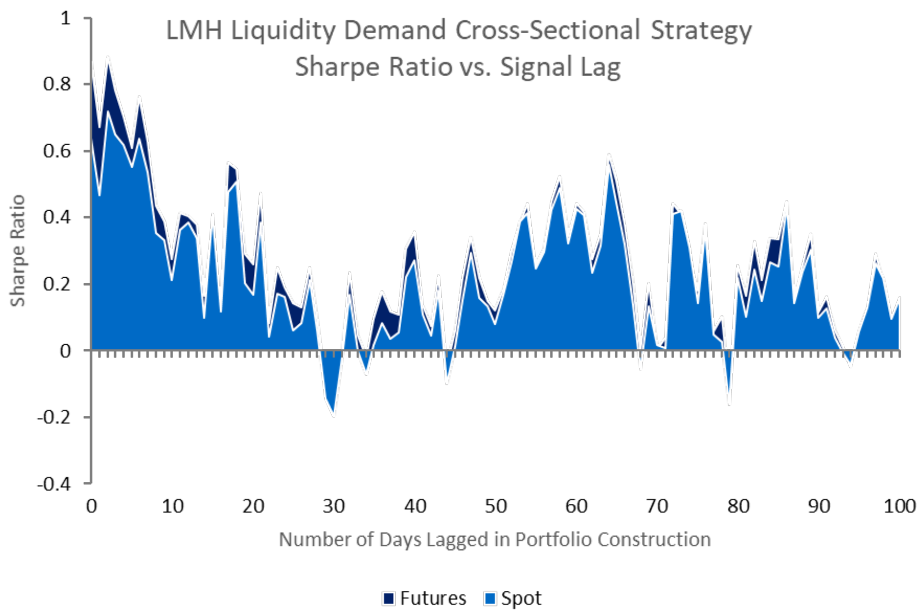
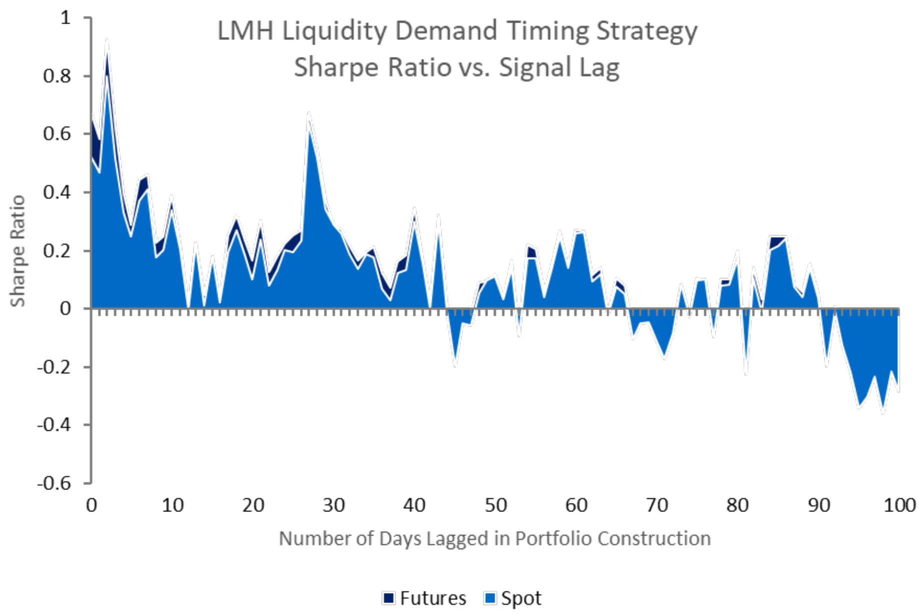


Figure IA.10. Signal Lagging and Strategy Performance

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.





IA.H. Securities Lending Fees

IA.H.1. Securities Lending Fee Data and Measure Construction

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 lending data is not available for a stock, we exclude it from our index-level calculations and re-normalize the index weight for each stock with data; this is equivalent to assuming that the stock with missing data has the same value as the index-weighted average of all remaining stocks. We also winsorize the resulting index level values at the 1st and 99 percentiles.

The MSF dataset has good coverage for our sample, as summarized in Table IA.XVIII. 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.

IA.H.2. Security Lending Fee Summary Statistics

Table IA.XIX present summary statistics of the annnualized index lending series. The average index lending fee is 47 basis points across the indices in our sample, and the average standard deviation of the index security lending fee is 17 basis points. The S&P 500 and DJIA indices have the lowest security lending fees (28 basis points on average), with standard deviations of 8 and 9 basis points, respectively, while the Russell 2000 and Spanish IBEX indices have the highest security lending fees (69 and 70 basis points on average), with standard deviations of 18 and 36 basis points.

The securities lending fee data presents some interesting insights for understanding futures-cash bases. First, bases are close to zero on average; however, security lending fees are positive. If dealers earned the full index security lending fee in their transactions, we may expect the basis to be exactly the negated value of the security lending fee. Given that this is not true on average, there are likely other important costs embedded in the basis that are not captured by securities lending fees. Second, securities lending fees display considerably less time-series variation than the basis. This indicates that lending fees may be useful for capturing some of the slower moving dynamics of the basis, but likely do not capture all factors that may move the basis.

IA.H.3. Basis Trading Strategy Adjusting for Security Lending Fees

Given the expected relationship between the futures-cash basis and security lending fees, an interesting question is whether our index security lending fee measure can account for the return predictability of bases. We evaluate this question by constructing a fee-adjusted measure of the basis for each index i by adding the basis and security lending fee together, $adjbasis_{i,t} = basis_{i,t} + fee_{i,t}$. Then, we form weekly-rebalanced trading strategies, as in our main analysis. If the lending fee explains the variation in the basis relevant for return predictability, then we expect the adjusted trading strategies to have muted performance.

The cross-sectional strategy formed using the adjusted basis earns an annualized Sharpe ratio of 1.02 in futures markets and 0.83 in spot markets. The timing strategy formed using the adjusted basis earns an annualized Sharpe ratio of 0.26 in the spot markets. Cross-sectional trading strategies formed by sorting on the unadjusted basis over the sample that we have lending fee data for have annualized Sharpe ratios of 0.92 and 0.76, and the corresponding timing strategies earn Sharpe ratios of 0.63 and 0.52 in futures and spot markets.

The results suggest that our security lending fee measure explains none of the cross-sectional return predictability of the basis, but may be able to explain some of the time-series return predictability. The results are consistent with the evidence in the main text, that the security lending fee measure is able to explain time-series variation in the basis, but has limited ability to explain cross-sectional variation. The modest explanatory power of our security lending fee measure for the basis and it's return predictability may stem from the fact that the security lending fee measure is an imperfect proxy for the true measure we are interested in, the marginal lending fee that dealers charge in lending transactions, and also the fact that while security lending fees may be especially important for some indices in our sample, they may be less relevant for other indices (e.g., the S&P500, where shares are easy to locate and borrow).

Table IA.XVIII. 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

Table IA.XIX. Securities Lending Fee Summary Statistics

The table reports the time-series average and the time-series standard deviation of the index security lending fee measure for each index in our sample. The fees are reported in annualized basis points.

	Average	**Standard Deviation**
AU	64	16
BD	44	16
CN	39	17
DJIA	28	9
ES	70	36
EUROSTOXX	45	18
FR	48	25
HK	57	24
IT	52	15
JP	53	21
NASDAQ	33	14
NL	43	9
SD	53	21
SW	42	14
UK	42	12
US	28	8
USRU2K	69	18
USSPMC	38	15
Average	47	17

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