

Liquidity and the Law of One Price: The Case of the Futures-Cash Basis

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ABSTRACT

Deviations from no-arbitrage relations should be related to market liquidity, because liquidity facilitates arbitrage. At the same time, a wide futures-cash basis may trigger arbitrage trades and, in turn, affect liquidity. We test these ideas by studying the dynamic relation between stock market liquidity and the index futures basis. There is evidence of two-way Granger causality between the short-term absolute basis and liquidity, and liquidity Granger-causes longer-term absolute bases. Shocks to the absolute basis predict future stock market liquidity. The evidence suggests that liquidity enhances the efficiency of the futures-cash pricing system.

THE LAW OF ONE PRICE is a fundamental building block of modern financial theory. Indeed, several well-known pricing relations in finance depend on the notion that two traded or synthesized instruments with the same future cash flows should trade at the same price. In practice, of course, market microstructure aspects may cause a temporary deviation of prices from their no-arbitrage values. For example, extreme order imbalances in a cash market may create inventory problems for market makers and cause temporary deviations of cash prices from the corresponding no-arbitrage prices implied by derivative markets.

Finance scholars have long recognized that deviations from no-arbitrage relations are related to the frictions associated with transacting, in particular to (il)liquidity indicators such as the bid–ask spread. Thus, financial market liquidity may play a key role in moving prices to an appropriate level, where the futures-cash basis is zero. At the same time, a wide basis may trigger arbitrage trading, which may, in turn, affect liquidity. In this paper, we explore these ideas by examining the joint dynamic structure of the futures-cash basis and stock market liquidity.

Liquidity is increasingly attracting attention from traders, regulators, exchange officials, and academics. Recent financial crises suggest that, at times,

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market conditions can be severe and liquidity can decline or even disappear.¹ Many microstructure studies are devoted to the measurement of and time variation in liquidity. The study of liquidity is often justified to a broader finance audience by arguing that liquidity shocks affect asset prices. Amihud and Mendelson (1986) and Jacoby, Fowler, and Gottesman (2000) provide theoretical arguments and empirical evidence to show how liquidity impacts stock returns in the cross-section, while Jones (2001) and Amihud (2002) show that liquidity predicts expected returns. Pastor and Stambaugh (2003) find that expected stock returns are cross-sectionally related to liquidity risk.

Our analysis of the link between the futures-cash basis and liquidity focuses on another potential reason why liquidity is relevant for financial theory. Specifically, we attempt to discern whether aggregate stock market liquidity affects and is affected by the futures-cash basis, and whether liquidity is related to deviations in the law of one price.

There have been many insightful previous studies of the basis² and various informal arguments have been offered about the relation between the basis and trading costs.³ To the best of our knowledge, however, there has not been any previous attempt to dynamically relate the basis to concrete measures of endogenous trading frictions such as stock market liquidity over a comprehensive time-period.⁴ Our empirical investigation involves the joint time-series of aggregate liquidity on the NYSE and the futures-cash basis associated with the NYSE composite index futures contract. A relatively long sample of over 3,000 trading days (1988 to 2002) allows for the possibility of reliable conclusions.

The motivation for our study derives in part from the earlier literature on the futures-cash basis and liquidity. First, as Kumar and Seppi (1994) point out, arbitrage activities, and hence, the basis, may be affected by liquidity. Furthermore, if the futures-cash gap induced by illiquidity is sufficiently wide, an illiquidity shock may have a lasting effect on the basis as arbitrageurs struggle to close the gap. In the reverse direction, market-wide order imbalances resulting from arbitrage trades in response to a wide basis may have a contemporaneous as well as a persistent impact on liquidity (Stoll (1978), O'Hara and Oldfield (1986), Chordia, Roll, and Subrahmanyam (2002)). Following these ideas, our

¹ "One after another, LTCM's partners, calling in from Tokyo and London, reported that their markets had dried up. There were no buyers, no sellers. It was all but impossible to maneuver out of large trading bets."—*Wall Street Journal*, November 16, 1998.

² See, for example, Modest and Sundaresan (1983), Kawaller, Koch, and Koch (1987), Yadav and Pope (1990), Chung (1991), Klemkosky and Lee (1991), Subrahmanyam (1991), Bessembinder and Seguin (1992), Chan (1992), Sofianos (1993), Miller, Muthuswamy, and Whaley (1994), Neal (1996), Barclay, Hendershott, and Jones (2003), and Wang (2003).

³ See, for example, Bodie, Kane, and Marcus (1993, pp. 738–740).

⁴ In an interesting paper, Bakshi, Cao, and Chen (2000) consider the frequency with which index option prices violate theoretical comparative statics. They do not, however, relate the liquidity of the cash market to these violations. Liquidity is key to arbitraging an index derivative as the cash instrument is a basket of many stocks. Bakshi, Cao, and Chen use data that span about 3 months; we consider the relation between the futures-cash basis and aggregate stock liquidity using about 15 years of data.

goal is to explore intertemporal associations between market liquidity and divergence of the futures and cash markets from their no-arbitrage relation.

It may be useful to cast the investigation in terms of a null and alternative hypothesis. Consider two scenarios: First, suppose that order flows in the cash and futures markets are virtually disconnected, and the basis is governed almost solely by quote updating on the part of market makers in the stock and futures markets; second, assume that arbitrageurs do not affect stock liquidity and their trades are not sensitive to liquidity. In either of these scenarios, the basis would bear little or no relation with liquidity. This forms our null hypothesis. On the other hand, if arbitrageurs have significant impact on liquidity, then their trades should be sensitive to liquidity, and their trades should affect liquidity. This forms our alternative hypothesis.

Of course, there is no reason to restrict attention to a contemporaneous link between the basis and liquidity; longer-term linkages and feedback would also be of interest. Foundational work in microstructure by Stoll (1978) and O'Hara and Oldfield (1986) suggests that price pressures created by individual stock order imbalances can have a lasting impact on liquidity. Chordia et al. (2002) empirically show that these inventory arguments apply to market-wide imbalances and market returns as well. The futures-cash basis, which is subject to order flow pressures induced by arbitrage trades, could therefore forecast future liquidity. In the reverse direction, suppose that the futures-cash gap widens considerably on a given day. Then the large volume of arbitrage trades required to close the gap may not happen instantly. This is because arbitrageurs may choose to spread their trades out over time to minimize price impact (Kyle (1985)), and such autocorrelated order imbalances would have persistent effects on liquidity.

Our analysis proceeds in two stages. First, we look for long-term relations between the basis and liquidity. To do this, we model the stochastic process of the basis, as in Brennan and Schwartz (1990), and then relate the mean reversion of the process to the average liquidity indicator over each contract's lifetime.

We then examine short-horizon (daily) time-series relations between the basis and liquidity. The raw time series of liquidity and the futures-cash basis are first expunged of deterministic time trends and calendar regularities (cf. Gallant, Rossi, and Tauchen (1992)). Then, vector autoregressions are fitted to the adjusted series in an effort to elucidate the dynamic interplay between liquidity and the basis.

The principal liquidity indicators used here are quoted and effective bid-ask spreads. While other measures of liquidity are potentially available, spreads have been the focus of much recent literature (e.g., Amihud and Mendelson (1986), Chordia, Roll, and Subrahmanyam (2000), Hasbrouck and Seppi (2001)), and are readily extractable over a long time period on a daily frequency.⁵

⁵ Some alternative liquidity proxies, such as those of Amihud (2002) and Pastor and Stambaugh (2003), are not readily available as daily measures.

Using a daily interval to analyze the joint dynamics of liquidity and the basis is, to some extent, arbitrary. Two justifications: First, dealer inventory considerations loom most significantly over rather short horizons, that is, daily as opposed to weekly or monthly; second, the daily horizon is long enough to reduce the influence of nonsynchronous trading.⁶

Our main results are as follows:

1. Over the lifetime of a futures contract, the basis mean-reverts faster when the market is more liquid.
2. There is two-way Granger causality between the 3-month absolute basis and liquidity, as measured by effective spreads.
3. Shocks to absolute bases are significantly informative in predicting the next day's bid-ask spreads.
4. Liquidity shocks forecast future shifts in the long-term basis, suggesting that liquidity affects arbitrageurs more in the relatively less active longer-term futures contracts.

A robustness check employs an alternative measure of illiquidity that accounts for the price impact of large trades, the effective spread associated with such trades. The central results continue to hold for this measure. They also continue to hold for an alternative basis obtained using the S&P 500 index future and either the underlying cash index or the corresponding SPIDER (the exchange traded basket of S&P 500 stocks). The results are stronger for the cash index, suggesting the relevance of trading costs in constructing a cash arbitrage position. In an attempt to identify other drivers of arbitrage costs, we investigate the role of short-term interest rates and find that the bi-directional relation between the basis and liquidity is preserved even after accounting for the effect of financing.

This evidence sheds new light on the literature that considers dynamic determinants of liquidity (viz., Hasbrouck and Seppi (2001), Chordia, Roll, and Subrahmanyam (2001)). Since the absolute basis provides information about future liquidity, shifts in the basis may change the aggregate cost of capital (viz., Amihud and Mendelson (1986)). Furthermore, the results suggest that illiquidity impedes the movement of futures and cash market prices toward the frictionless ideal of a zero basis.

Section I below describes the data. Section II presents evidence on the relation between the speed of the mean reversion in the basis and liquidity. Section III discusses adjustment of the basis and liquidity series to account for time-trends and other regularities. Section IV discusses evidence from vector autoregressions. Section V considers various robustness checks. Section VI concludes and suggests further investigations.

I. Data

This section provides data sources and explains the methods used for computing the futures-cash basis and the liquidity indicators.

⁶ This issue is revisited in Section V.

A. Computation of the Basis

Let F be the current index futures price, S be the cash stock market index, r the risk-free rate for lending and borrowing over the remaining life of the contract, t the time to contract expiration, and δ the dividend yield over the contract's lifetime. As in MacKinlay and Ramaswamy (1988), the absolute value of the relative index futures basis (henceforth, termed the "absolute basis") can be defined as

$$\frac{|Fe^{-(r-\delta)t} - S|}{S}. \quad (1)$$

In a frictionless world, the above quantity should be precisely zero. However, it is well known from earlier work (e.g., Brennan and Schwartz (1990)) that the basis exhibits considerable time-series variation.

The basis is constructed empirically with the following components: F is the closing futures price on the NYSE composite index futures contract, while S is the closing value of the NYSE composite index. The riskless rate r is the continuously compounded yield on a Treasury Bill maturing as close to the futures expiration date as possible, and, if necessary, the yield is extrapolated from the last day of the bill's life to the end of the contract. The dividend yield δ is the (continuously compounded) annual yield on the NYSE composite index (obtained from CRSP) updated in January of every year.⁷ The NYSE composite index futures contract expires on the third Friday in March, June, September, or December.⁸

Four different time-series of the bases can be constructed by starting with a contract having X months to maturity and rolling over every third Friday of March, June, September, and December into a successive contracts with the same original time to maturity, where $X = 3, 6, 9$, or 12. We focus on the first three series, because the fourth is inactively traded (an average volume of about two contracts per day) and is not likely subject to arbitrage forces because of its lack of liquidity.⁹ Henceforth, the three shorter series are called the 3-, 6-, and 9-month bases, respectively.

⁷ There inevitably is some error associated with the measurement of both the risk-free rate and the dividend yield. However, the errors should be small (in particular, the dividend yield on a basket such as the NYSE composite index should not fluctuate much from day to day). Furthermore, it seems unlikely that any measurement error would be related to liquidity, our variable of interest. Nonetheless, to mitigate possible measurement error problems, we use the measured values of the above variables on the right-hand side of adjustment regressions prior to conducting vector autoregressions. Controlling for the measured values of these variables allows us to capture the component of the measurement error in the basis (the left-hand variable).

⁸ All contracts officially expire on Friday. However, within the futures data set (obtained from www.normanshistoricaldata.com), in some cases there was no trading on Friday and we substituted Thursday as the last day of trading.

⁹ There is a slight asynchronicity between the hours of operation of the NYSE and the New York Board of Trade (where the futures contracts trade). Specifically, while both exchanges open at the same time (9:30 am), the NYSE closes at 4 pm, which is 15 minutes prior to the close of the futures exchange. While this will undoubtedly introduce some measurement error in the basis, it should not affect our inferences because there is no reason to suspect a relation between the error induced by a slightly later closing of the futures market and aggregate stock market liquidity.

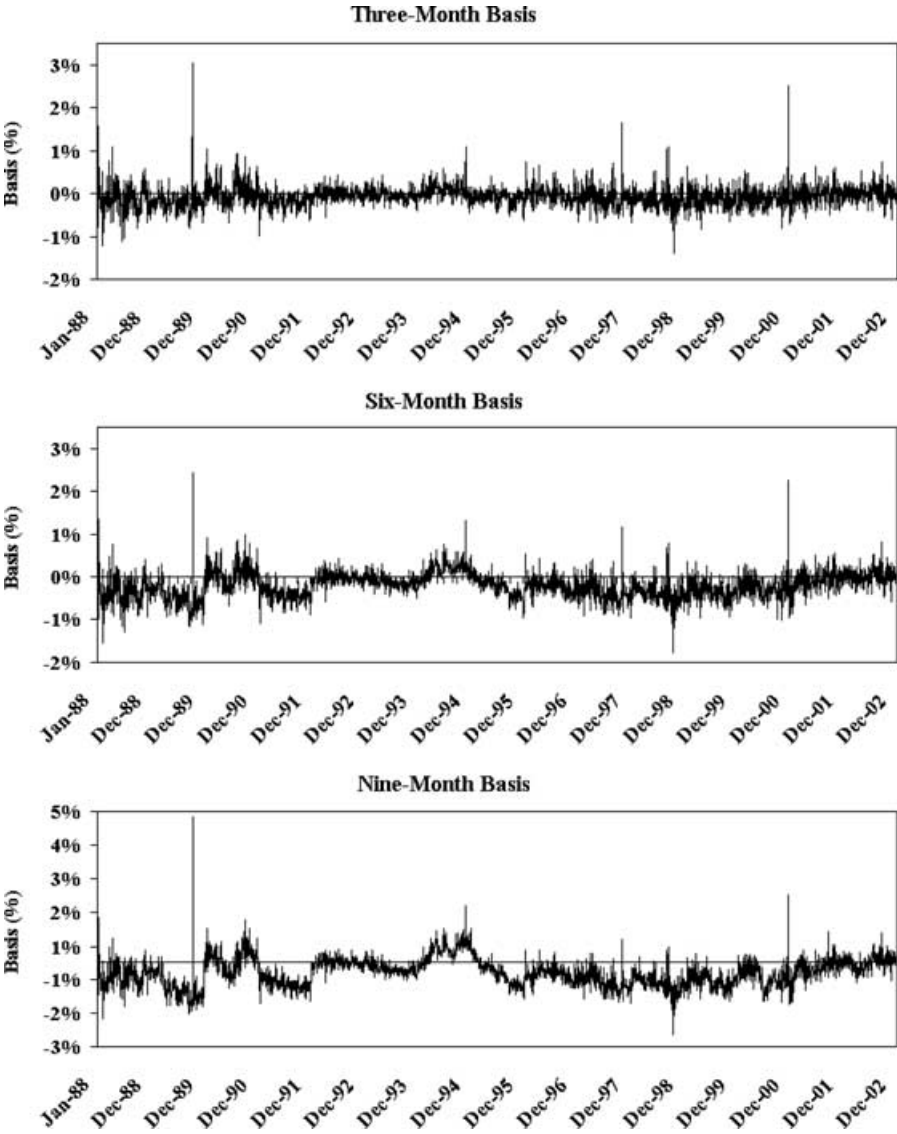


Figure 1. NYSE composite index futures bases over time. Absolute bases for the 3-, 6-, and 9-month NYSE composite index futures contracts are plotted for the period 1988 to 2002, inclusive.

Figure 1 plots the three bases over the sample period. The basis in each case appears fairly stationary though the 9-month basis exhibits larger deviations from zero than the other two (notice the differences in scale of the vertical axes).

B. Stock Liquidity Data

An aggregate NYSE liquidity index on a daily basis for the period 1988 to 2002 is constructed as follows:

1. To be included, a stock is required to be present at the beginning and at the end of the year in both the CRSP and the intraday databases.
2. To reduce the impact of firms entering the sample mid-year, if the firm changes exchanges from Nasdaq to NYSE during the year (no firms switched from the NYSE to the Nasdaq during the sample period), it is dropped from the sample for that year.
3. Because their trading characteristics might differ from ordinary equities, certificates, ADRs, shares of beneficial interest, units, companies incorporated outside the United States, Americus Trust components, closed-end funds, preferred stocks, and REITs are expunged.¹⁰
4. To avoid the undue influence of high-priced stocks, which have inordinately large spreads, if the price at any month-end during the year is greater than \$999, the stock is deleted from the sample for the year.

Intraday data are purged for one of the following reasons: trades out of sequence, trades recorded before the open or after the closing time, and trades with special settlement conditions (because they might be subject to distinct liquidity considerations). A preliminary investigation reveals that auto-quotes (passive quotes by secondary market dealers) have been eliminated in the ISSM database but not in TAQ. This causes the quoted spread to be artificially inflated in TAQ. Since there is no reliable way to filter out auto-quotes in TAQ, only BBO (best bid or offer)-eligible primary market (NYSE) quotes are used. Quotes established before the opening of the market or after the close are discarded. Negative values for bid-ask spreads, transaction prices, and quoted depths are discarded. Each bid-ask quote included in the sample is matched to a transaction; specifically, following Lee and Ready (1991) any quote less than 5 seconds prior to the trade is ignored and the first one at least 5 seconds prior to the trade is retained.

Spreads are not scaled by price. This is to avoid attributing movements in stock prices to movements in liquidity (recall that the stock price already forms the denominator of the absolute basis, which is based on MacKinlay and Ramaswamy (1988)). Such a procedure is further justifiable because we are interested in the dynamic relation between liquidity and the absolute basis (as opposed to their cross-sectional relation.) We have verified, however, that the principal results are robust to using a proportional spreads (i.e., scaled by price).

¹⁰ As the referee noted, most arbitrage trade probably involves only relatively liquid stocks (Neal (1996)). Nonetheless, we constructed an alternative index that includes all NYSE stocks for the period 1993 to 2002. Such an index could not be constructed for the period 1988 to 1992 because of data unavailability (the pre-TAQ ISSM data were not accessible to the study's authors). The results are largely robust using this alternative index and the shorter sample period; they are available upon request.

For each stock the following variables are calculated (these variables have also been the focus of earlier research on long-horizon liquidity; see e.g., Chordia et al. (2001)):

1. Quoted spread: the difference between the asked and the bid quote.
2. Effective spread: twice the absolute distance between the transaction price and the mid-point of the prevailing quote.

An initial scanning of the intraday data reveals a number of anomalous records that appear to be keypunching errors. Filters are applied to the transaction data by deleting records that satisfy the following conditions:

1. Quoted spread $> \$5$
2. Effective spread/quoted spread > 4.0
3. Proportional effective spread/proportional quoted spread¹¹ > 4.0
4. Quoted spread/mid-point of bid–ask quote > 0.4 .

These filters removed less than 0.02% of all stock transaction records. The spreads are averaged across the day to obtain stock illiquidity measures for each day. To avoid excessive variation in the sample size, stocks are required to have traded for a minimum of 100 days in a year to be included in the sample for that year. Days for which stock return data were not available from CRSP are dropped from the sample. The dates of October 25, 1989 and September 4, 1991 are also dropped from the sample because of transparent reporting errors. On the former date, there are no data at all, and on the latter ISSM recorded only quotes but no transactions. In addition, data are not available for the period from September 11 to September 14, 2001 (neither for the stock liquidity measures nor for the basis) because of market closures and disruption following the events in New York City. The daily spread measures are averaged, value-weighted, across stocks (with weights proportional to market capitalizations at the end of the previous year) to obtain the aggregate market illiquidity measures.

Figure 2 plots these aggregate quoted and effective spreads. They exhibit a downward trend throughout the sample period. In addition, there are two significant drops corresponding to the reduction in minimum tick size, first from eighths to sixteenths and then to cents. Because of the nonstationary nature of these liquidity constructs we will adjust them for deterministic time trends, calendar regularities, and discrete reductions in the minimum tick size prior to using the adjusted series in vector autoregressions involving the basis variables.

Since deviations from the no-arbitrage relation can arise in either direction, the *absolute* basis is the most sensible object of inquiry. Table I presents summary statistics for the absolute bases and liquidity variables. In unreported *t*-tests, we find that all of the means are statistically significant at the 5% level

¹¹ The proportional spreads in condition 3 are obtained by dividing the unscaled spreads by the mid-point of the prevailing bid–ask quote.

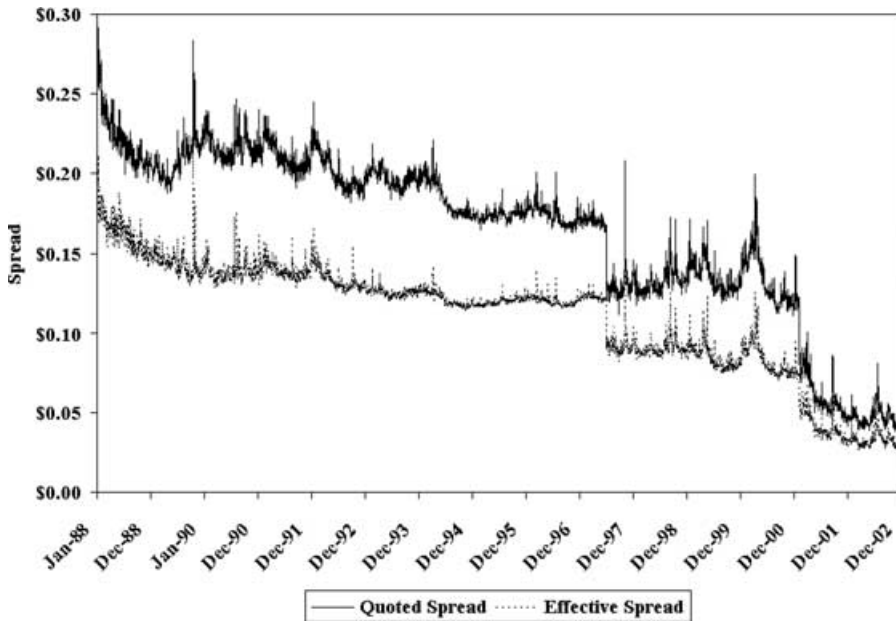


Figure 2. Liquidity indicators over time. NYSE value-weighted quoted and effective spreads are plotted for the period 1988 to 2002, inclusive.

Table I
Summary Statistics for NYSE Futures-Cash Bases
and Liquidity Measures

Summary statistics are for absolute bases (in percentages relative to the cash index value) for the 3-, 6-, and 9-month NYSE composite index futures contracts, and (in dollars) for the NYSE value-weighted quoted and effective spreads; daily data, 1988 to 2002 inclusive.

Variable	Mean	Median	Standard Deviation
3-month absolute basis	0.170%	0.131%	0.165%
6-month absolute basis	0.240%	0.205%	0.189%
9-month absolute basis	0.347%	0.303%	0.260%
Quoted spread	\$0.164	\$0.175	\$0.053
Effective spread	\$0.110	\$0.121	\$0.036

or less. The mean value of the absolute basis across the three series, however, is only about 0.3%, which suggests that, on average, arbitrage activities are quite effective. Table I also reveals that both the mean and volatility of the absolute basis increase with the remaining term of the futures contract. The average value of the quoted spread is about 16 cents. The quoted spread is more than 5 cents larger than the effective spread, indicating that many transactions take place within the quoted spread.

II. Preliminary Evidence

Our initial evidence relates the basis and average liquidity over a contract's lifetime. Specifically, we ask whether the mean reversion in the basis is faster when the market is more liquid, which should be the case if arbitrage activity is more intense during such periods.

Brennan and Schwartz (BS) (1990) postulate a Brownian Bridge process for the basis:

$$dB(t) = -\frac{\mu B}{\tau} dt + \gamma dz, \quad (2)$$

where $B(t)$ denotes the *signed* basis at time t , τ denotes the time to maturity, μ the speed of mean reversion, and γ the instantaneous standard deviation of the process. BS show how to estimate the parameters μ and γ using maximum likelihood techniques; details appear in Appendix A. We estimate these parameters for the bases associated with every contract and also compute average values of the liquidity measures over each contract's lifetime.

Table II reports correlation coefficients between the estimated speed of mean reversion μ and the average value of the liquidity measure over contract lifetimes. As can be seen, in every instance the reversion parameter's estimate is negatively related to both quoted and effective spreads, and the correlation is highly significant for the 6- and 9-month bases. This suggests that the signed basis mean reverts more quickly when the market is more liquid.

Though it supports a relation between the basis and liquidity, the evidence in Table II is long run oriented in the sense that it employs averages over contracts' lifetimes. We also want to consider dynamic and persistent short-term relations between the absolute basis and liquidity, including the possibility that they forecast each other. For these purposes, vector autoregressions (VARs) are appropriate. In large part, the remainder of the paper explains VARs in the present context and reports estimates obtained from VARs.

III. Adjustment Regressions and Initial Evidence on the Basis-Liquidity Relation

To perform vector autoregressions, it is desirable to first remove common regularities and trends from the time series in order to minimize the possibility of spurious conclusions. Prior research (Chordia et al. (2001)) found that spreads exhibit time-trends and calendar regularities. It seems plausible that the absolute basis could also exhibit such phenomena. For example, the increased risk of holding positions over the weekend could cause higher absolute bases toward the end of the week. To mitigate such problems, the raw time-series are first expunged of deterministic variation (see Gallant et al. (1992) for a similar approach to adjusting the series of trading volume). Since little is known about seasonalities or regularities in the stock-futures basis, this analysis is of independent interest.¹² Subsequently (Section IV), innovations (residuals)

¹² The impact of the adjustment process is explored in Section V.

Table II
Correlation between Basis Mean Reversion and Liquidity

The correlation is between average quoted and effective spreads and each contract's estimated mean reversion parameter assuming a Brownian Bridge process for the basis. Daily data over the 1988 to 2002 period are used for the estimation (*p*-values are in parentheses).

	Quoted Spread	Effective Spread
3-month basis	-0.187 (0.169)	-0.182 (0.178)
6-month basis	-0.474 (0.000)	-0.443 (0.000)
9-month basis	-0.273 (0.028)	-0.255 (-0.049)

from the adjustment regressions are related in a vector autoregression (VAR). To reiterate from Section II, the motivation for the VAR approach is that bi-variate causality is likely. When the stock market is illiquid, arbitrageurs may have difficulty closing the gap between the two markets. In the reverse direction, a large inventory imbalance caused by arbitrage trades could result in illiquidity.

The following variables are used to adjust the raw basis series: (i) a Friday dummy to account for increased costs of holding positions through the weekend, (ii) 11 calendar month dummies for January through November, (iii) a dummy for days prior to major holidays: Thanksgiving, Christmas Eve, and July 4, (iv) for the 3-month basis, four dummies for the 4 days prior to expiration, to control for any maturity-related effects (v) a time trend and the square of the time trend to remove any long-term trends,¹³ and (vi) the difference between the risk-free rate and the dividend yield to account for any errors in the measurement of these quantities. For spreads, explanatory variables include day-of-the-week, month-of-the-year, and holiday dummies, linear and quadratic time trends, and two dummies to account for the post-16th period (i.e., including the period following the shift in minimum tick size from 1/8 to 1/16 on June 24, 1997) and the postdecimalization period (on and after January 29, 2001).

Table III presents coefficients from the adjustment regressions for the absolute bases. The difference between the risk-free rate and dividend yield is positive and significant for all three contracts. This variable is introduced in an effort to correct measurement error in the borrowing/lending rate of arbitrageurs and in the dividend yield.

Calendar time effects also are discernible in that the absolute basis tends to be lower in late summer. This phenomenon is to be understood in conjunction with the finding that trading volume also tends to be abnormally low in August (see Gallant et al. (1992)). The secular regularity of lower trading volume in late summer could result in smaller price pressures, and consequently, smaller deviations of the basis from zero.

¹³ The time trends are orthogonalized; that is, the linear time index t goes from -1 at the beginning of the sample to 1 at the end of the sample, whereas the quadratic term equals $(3t^2 - 1)/2$.

Table III
Absolute Basis Adjustment

In these OLS regressions, the dependent variable is the absolute basis for a NYSE composite index futures contract. The time period is 1988 to 2002 inclusive. Dummy variables are included for Friday and for months of the year. RemTrm is the number of days until contract expiration, with 1 representing the last trading day. Holiday-1 is a dummy for the trading day prior to Thanksgiving, Christmas, or July 4. Time and Time**2 are orthogonalized linear and quadratic time trends, respectively. Rf-Dyld is the difference between the estimated risk-free rate and the dividend yield. All coefficients are multiplied by 100.

Variable	Maximum Maturity of Futures Contract (Months)					
	Three		Six		Nine	
	Coefficient	<i>T</i>	Coefficient	<i>T</i>	Coefficient	<i>T</i>
Friday	0.012	1.76	0.009	1.20	0.011	1.12
January	-0.018	-1.37	-0.065	-4.42	-0.106	-5.41
February	-0.041	-3.06	-0.111	-7.44	-0.159	-7.98
March	-0.024	-1.88	-0.092	-6.35	-0.157	-8.13
April	0.005	0.37	-0.043	-2.94	-0.092	-4.68
May	-0.032	-2.47	-0.074	-5.07	-0.118	-6.09
June	-0.013	-1.02	-0.064	-4.43	-0.113	-5.80
July	-0.022	-1.69	-0.039	-2.69	-0.044	-2.28
August	-0.037	-2.88	-0.069	-4.81	-0.115	-6.01
September	-0.015	-1.14	-0.031	-2.13	-0.050	-2.56
October	0.024	1.85	0.025	1.72	0.035	1.80
November	-0.027	-2.04	-0.024	-1.62	-0.004	-0.21
RemTrm = 1	0.008	0.31				
RemTrm = 2	-0.067	-3.16				
RemTrm = 3	-0.038	-1.79				
RemTrm = 4	-0.049	-2.28				
Holiday-1	-0.032	-1.50	0.022	0.77	0.043	1.12
Time	-0.005	-1.18	0.028	5.38	0.050	7.07
Time**2	0.043	7.30	0.007	1.02	0.009	1.00
Rf-DYld	1.458	8.38	2.683	13.76	4.582	17.58
Intercept	0.154	14.76	0.220	19.30	0.303	19.74
Adjusted- <i>R</i> ²	0.048		0.080		0.123	

Note that the coefficients for month-of-the-year regularities in the adjustment regression are usually more significant and of larger absolute magnitudes for the longer-term bases. Indeed, the August coefficient for the 9-month basis is more than double that for the 3-month basis, and is also more significant. Furthermore, the explanatory power of the regression is also larger for the longer-term bases. This observation makes intuitive sense; since contracts with longer times to maturity would tend to be less liquid; one would expect more predictable deviations of the basis from zero for such contracts.¹⁴

Table IV reveals that quoted spreads are lower on Monday through Wednesday and are also lower in most months relative to January (the omitted

¹⁴ The average trading volumes for the 3-, 6- and 9-month bases are, respectively, 3,037, 455, and 14. These numbers are all statistically different from each other at the 5% level, and clearly suggest decreasing contract liquidity with increasing maturity.

Table IV
Spread Adjustment

In these OLS regressions, the dependent variables are the daily NYSE value-weighted quoted and effective spreads from 1988 to 2002, daily observations. Dummy variables are included for days of the week and months of the year. Holiday-1 denotes the trading day prior to Thanksgiving, Christmas, or July 4. Post-16th and postdeci denote periods following a reduction in the minimum tick size to 1/16 (on June 24, 1997) and a further reduction to \$0.01 (on January 29, 2001). Time and time**2 are orthogonalized linear and quadratic time trends, respectively. All coefficients are multiplied by 100.

Variable	Quoted Spread		Effective Spread	
	Coefficient	<i>T</i>	Coefficient	<i>T</i>
Monday	-0.176	-3.16	-0.064	-1.76
Tuesday	-0.186	-3.41	-0.097	-2.70
Wednesday	-0.116	-2.13	-0.080	-2.24
Thursday	-0.072	-1.32	-0.071	-1.99
February	-0.031	-0.36	0.046	0.82
March	-0.223	-2.67	-0.119	-2.17
April	-0.168	-1.98	-0.007	-0.12
May	-0.678	-8.05	-0.294	-5.30
June	-0.906	-10.78	-0.407	-7.37
July	-0.840	-9.94	-0.422	-7.59
August	-0.898	-10.78	-0.423	-7.72
September	-1.086	-12.70	-0.578	-10.27
October	-0.583	-6.98	-0.225	-4.11
November	-0.931	-10.94	-0.535	-9.57
December	-0.850	-10.03	-0.464	-8.33
Holiday-1	0.055	0.56	0.026	0.41
Post-16th	-2.574	-29.32	-2.181	-37.77
Postdeci	-6.459	-64.80	-4.441	-67.73
Time	-4.427	-50.32	-2.835	-48.98
Time**2	0.172	2.43	0.633	13.56
Intercept	18.85	239.2	12.68	244.6
Adjusted- <i>R</i> ²	0.960		0.963	

month).¹⁵ Higher spreads in January might be due to imbalances created by reallocations to speculative stocks by institutional money managers after window-dressing in December. Positive order flow from individual investors' buying activity after year-end cash inflows such as bonuses may also contribute to the "January" effect in spreads. The effect of early fall on spreads is large; in absolute terms, the coefficient for the quoted spread in September is about six times as large as the coefficient in April; the corresponding ratio for the effective spread is even larger. These patterns are intriguing and warrant further analysis in future research.

There was a significant reduction in spreads after the minimum tick size was reduced from 1/8 to 1/16 and a further reduction after decimalization.

¹⁵ The coefficients are negative in all months (relative to January) and are significant except for February and April.

Table V
Correlation Matrix for Adjusted Absolute Bases
and Liquidity Measures

Correlations are presented between each measure of the adjusted absolute basis (ABAS_x, where *x* represents the basis horizon in months) and adjusted quoted and effective spreads (QSPR and ESPR, respectively). The adjusted series are residuals from the regressions in Tables III and IV. All coefficients are significant at the 5% level.

	ABAS3	ABAS6	ABAS9	QSPR	ESPR
ABAS3	1.000	0.789	0.498	0.158	0.199
ABAS6	0.789	1.000	0.807	0.112	0.109
ABAS9	0.498	0.807	1.000	0.046	0.048
QSPR	0.158	0.112	0.046	1.000	0.621
ESPR	0.199	0.109	0.048	0.621	1.000

In addition, spreads exhibit a strong secular downtrend. The behavior of the quoted and effective series is similar, and the explanatory power of the spread regressions is high.

The augmented Dickey–Fuller test strongly rejects the existence of a unit root for all five adjusted time series (three for the absolute basis, and two for spreads) at *p*-values less than 0.001. Hence, there is no evidence that the adjusted series are nonstationary. For the remainder of the paper, these adjusted series are used in all tests, and references to the original variables actually refer to the adjusted values, the residuals from the regressions in Tables III and IV.

Table V presents a correlation matrix for the three adjusted absolute bases (denoted ABAS3, ABAS6, and ABAS9) and the two adjusted spreads, quoted and effective (QSPR and ESPR). All correlations are statistically significant at the 5% level. The three absolute bases series are highly correlated. In addition, correlations of the bases with spreads are all positive, suggesting commonality. Correlations of the 3-month absolute basis are stronger with effective spreads than with quoted spreads, suggesting that the effective spread, which accounts for transactions executing within and outside the quotes, has a stronger link with the short-term basis.

As a preamble to the analysis of whether shocks to the absolute basis have a lasting effect on liquidity and vice versa, Table VI presents coefficients from OLS regressions of the absolute bases on one lag of the spreads and vice versa. The results indicate that the coefficient of the lagged effective spread is highly significant in explaining the shorter-term bases.¹⁶ In the reverse regression of spreads on lags of the absolute bases, lags of the two shorter-term absolute bases are significant in explaining spreads. In totality, the results of Tables V

¹⁶ An issue is whether the small sample bias discussed by Stambaugh (1999) and Amihud and Hurvich (2004) is a potential concern, since the right-hand side variables in Table VI are persistent. However, there are more than 3,700 observations, suggesting that this is not likely a serious problem. In fact, using the Amihud and Hurvich (2004) correction leaves the Table VI results virtually unchanged; results are available upon request.

Table VI
OLS Regression Coefficients

Regression results are presented for each measure of the adjusted absolute basis (ABAS_x, where *x* represents the basis horizon in months) on one lag of adjusted quoted and effective spreads (QSPR and ESPR, respectively), and vice versa. The adjusted series are residuals from the regressions in Tables III and IV. In Panel A, the coefficients are multiplied by 100.

Panel A: Absolute Bases as Dependent Variables					
Dependent Variable	Independent Variable: Lag(QSPR)		Independent Variable: Lag(ESPR)		
	Coefficient	<i>T</i>	Coefficient	<i>T</i>	
ABAS3	1.383	5.59	2.210		5.88
ABAS6	1.209	4.32	1.025		2.41
ABAS9	0.392	1.05	−0.230		−0.40

Panel B: Liquidity Measures as Dependent Variables						
Dependent Variable	Independent Variable: Lag(ABAS3)		Independent Variable: Lag(ABAS6)		Independent Variable: Lag(ABAS9)	
	Coefficient	<i>T</i>	Coefficient	<i>T</i>	Coefficient	<i>T</i>
QSPR	1.046	9.95	0.632	6.75	0.098	1.39
ESPR	0.858	12.51	0.409	6.63	0.029	0.62

and VI point to the notion that the shorter-term absolute bases and liquidity are jointly determined, possibly because arbitrage is more likely to take place in the relatively more active shorter-term contracts. We now turn to vector autoregressions, which allow for a richer dynamic structure between the bases and liquidity measures.

IV. Vector Autoregressions

The input data for VAR estimation are the adjusted series (i.e., the residuals) from the first-stage regressions described in the previous subsection.¹⁷ The

¹⁷ The reader may wonder to what extent bid–ask bounce affects the results. This phenomenon pertains to individual assets and is unlikely to be pronounced for a value-weighted index consisting of over 1,500 stocks. Also, index futures contracts are extremely liquid instruments, so bid–ask effects should be small. This is supported empirically by the daily first order autocorrelation in the 3-month futures price change series, which is only -0.021 ($p = 0.21$). The corresponding autocorrelations for the 6- and 9-month series are also statistically indistinguishable from zero. Later results indicate that the lagged absolute basis even predicts market depth (with or without controlling for the spread), and there is no reason why depth should be influenced by bid–ask bounce. Also, it is known that liquidity is low on days of heavy selling (Chordia et al. (2001)), suggesting the possibility that low liquidity may be accompanied by an artificially high absolute basis due to trades hitting the bid in the index. In this case, however, the basis should tend to narrow the next day as prices bounce back. There is no evidence that the absolute basis decreases after days of high spreads, nor is there any evidence that the basis is significantly wider on days with low (highly negative) returns. Finally, in many cases, the basis has a persistent impact on spreads and vice versa, a finding unlikely to be related to bid–ask phenomena. It appears that bid–ask bounce is not material here.

Table VII
Vector Autoregressions

Vector autoregressions pair each measure of the adjusted absolute basis (ABAS_x, where *x* represents the basis horizon in months) with adjusted quoted and effective spreads (QSPR and ESPR respectively). The adjusted series are residuals from the regressions in Tables II and III. The table presents correlations in VAR innovations (Panel A) and both chi-square statistics and *p*-values (in parentheses) of pairwise Granger-causality tests between the endogenous variables (Panel B).

Panel A: Correlations between VAR Innovations					
	ABAS3	ABAS6	ABAS9		
QSPR	0.126	0.082	0.099		
ESPR	0.158	0.102	0.141		

Panel B: Granger-Causality Tests (Null Hypothesis: Row Variable Does Not Granger-Cause Column Variable)					
	ABAS3	ABAS6	ABAS9	QSPR	ESPR
ABAS3	—	—	—	36.76 (0.00)	51.32 (0.00)
ABAS6	—	—	—	15.21 (0.02)	23.11 (0.00)
ABAS9	—	—	—	7.47 (0.28)	11.12 (0.09)
QSPR	12.83 (0.05)	3.179 (0.79)	21.99 (0.00)	—	—
ESPR	18.15 (0.01)	3.134 (0.79)	39.54 (0.00)	—	—

number of lags is determined by the Akaike and Schwarz information criteria. When these two criteria indicate different lag lengths, the lesser lag length is chosen for the sake of parsimony. Typically, the slopes of the information criteria (as a function of lag length) are quite flat for longer lags, so the choice of shorter lag lengths is further justified. Six bivariate VARs are estimated, pairing each of the three absolute basis measures (3-, 6-, and 9-months) with the two liquidity measures (quoted and effective spreads). The information criteria imply a lag length of 6 days for all VARs.

Panel A of Table VII reports pairwise correlations of innovations (residuals) from each of the six bivariate VARs. They are all positive with magnitudes ranging from about 0.08 to 0.16 and they are all statistically significant at the 5% level. They are slightly higher for effective spreads, again suggesting that effective spreads are more relevant estimates of arbitrage costs. Overall, this panel represents further evidence that illiquidity is positively associated with deviations from zero in the futures-cash basis; alternatively, that high stock market liquidity facilitates narrowing of the basis.

Table VII also reports pairwise Granger-causality tests. For the null hypothesis that variable *i* does not Granger-cause variable *j*, we test whether the lagged coefficients of *i* are jointly zero when *j* is the dependent variable in the VAR. In

Panel B of Table VII, the cell associated with the i th row variable and the j th column variable shows the chi-square statistic associated with this test.

The 3- and 6-month absolute bases Granger-cause quoted and effective spreads. Reverse causality running from both spreads is found for the 9- and the 3-month bases.¹⁸ Spreads do not Granger-cause the 6-month absolute basis. The evidence is largely consistent with liquidity concerns being more relevant for arbitrageurs in long-term, relatively less-active contracts.¹⁹ The results also reveal that absolute basis innovations for shorter-term contracts have a stronger effect on liquidity, perhaps because arbitrage activities are more intense in such contracts.²⁰ Also, as in Table V, the results depict stronger relations with the effective spread, which accounts for trading costs across both large and small orders.

However, not all the results in Table VII lend themselves to easy interpretation; for example, the effective spread Granger-causes the 3- and 9-month absolute bases, but not the 6-month. But Granger causality is based on a single equation. A clearer picture can potentially be provided by impulse response functions (IRFs), which account for the full dynamics of the VAR system.

An IRF traces the impact of a one-time, unit standard deviation, positive shock to one variable (henceforth termed simply a “shock” or “innovation” for expositional convenience) on the current and future values of the endogenous variables. Since the innovations are correlated (as shown in Panel A of Table VII), they need to be orthogonalized, so we use the inverse of the Cholesky decomposition of the residual covariance matrix to orthogonalize the impulses. Results from the IRFs are generally sensitive to the specific ordering of the endogenous variables.²¹ However, conclusions about our IRFs turn out to be insensitive to the ordering, and also robust to the computation of generalized impulse responses (Pesaran and Shin (1998)). In the following results, the absolute basis variables are always placed first in the ordering.

Figures 3 through 6 depict responses of the liquidity and basis measures to a unit standard deviation shock in a particular variable traced forward over a period of 6 days (i.e., the lag length of the VAR). Monte Carlo two-standard-error bands (based on 1,000 replications) are provided to gauge the statistical significance of the responses. Period 1 in the IRFs represents the contemporaneous response, whereas subsequent periods represent lagged responses. The vertical axes are scaled to the measurement units of the responding variable. The impulse responses generally decay over time, confirming the unit root tests that indicate stationarity.

¹⁸ The p -value up to the third decimal place for the Granger causality running from QSPR to ABAS3 is 0.046.

¹⁹ Refer to Footnote 14.

²⁰ The notion that market frictions can affect the efficacy of arbitrage is suggested in Mitchell, Pulvino, and Stafford (2002), Lamont and Thaler (2003), Sadka and Scherbina (2004), and Hou and Moskowitz (2005). We explore this notion as well as the reverse, namely, that exploitation of arbitrage opportunities can impact an endogenous market friction, liquidity.

²¹ VAR coefficient estimates (and, hence, the Granger-causality tests) are unaffected by the ordering of variables.

Response to Cholesky One S.D. Innovations ± 2 S.E.

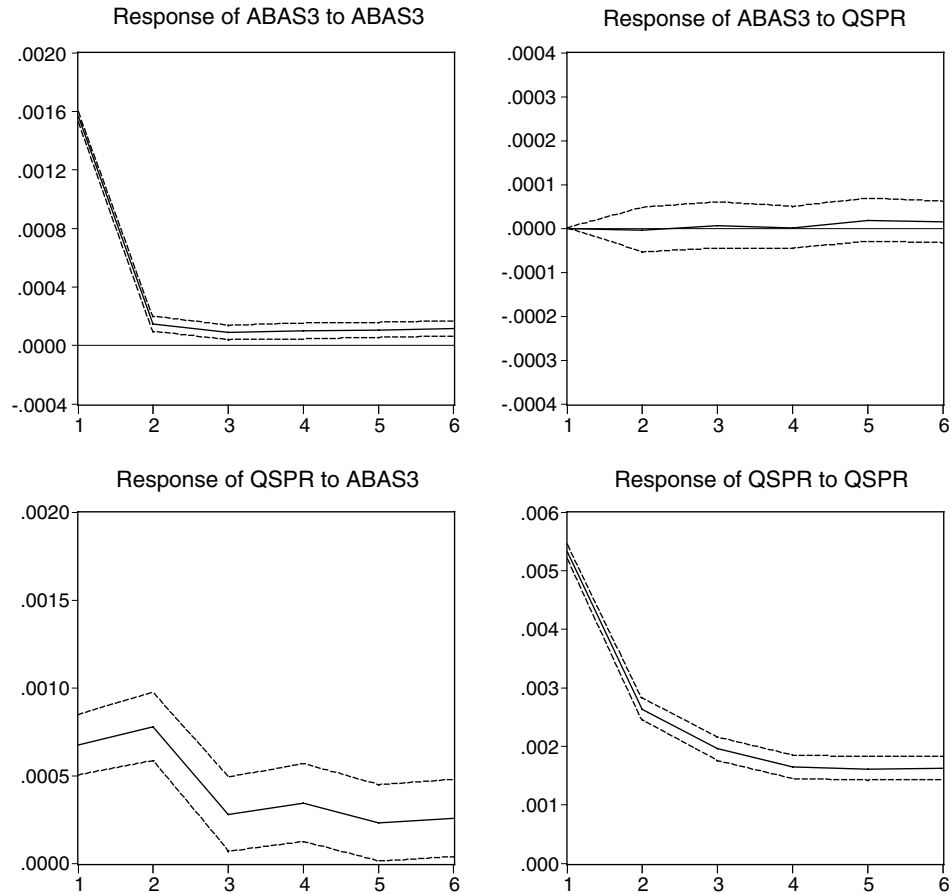


Figure 3. Impulse response functions for the bivariate VAR with the 3-month absolute basis (ABAS3) and the quoted spread (QSPR). Impulse responses are presented for the vector autoregression that pairs the 3-month absolute basis with the NYSE quoted spread from 1988 to 2002 (both variables are adjusted for time trends and other regularities). Monte Carlo two-standard-error bands (based on 1,000 replications) are provided along with the estimated responses.

It can be seen that shocks to a variable are informative in predicting future values of that same variable in every instance. This confirms that both spreads and absolute bases are persistent. With regard to cross-effects, the IRFs are largely consistent with the Granger-causality results. Innovations in the 3-month absolute basis have a lasting and significantly positive effect on both spread measures (lower left panel of Figures 3 and 4) thereby indicating that the absolute basis forecasts future stock market liquidity. Specifically, the results

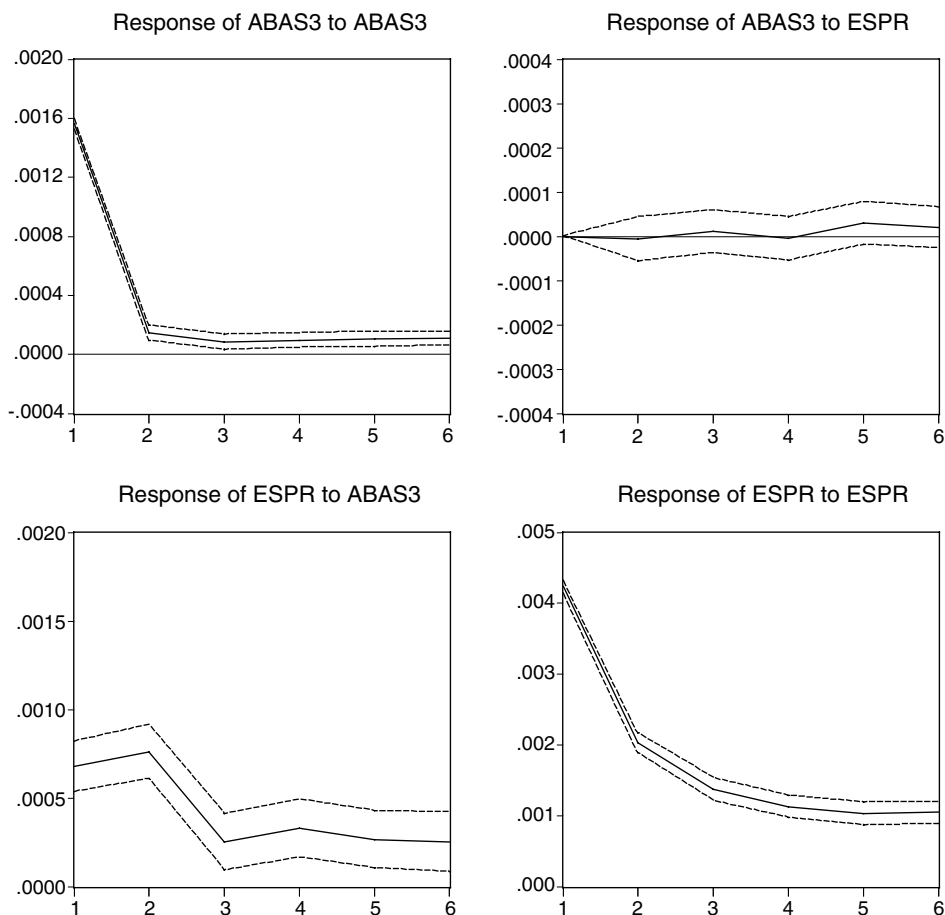
Response to Cholesky One S.D. Innovations ± 2 S.E.

Figure 4. Impulse response functions for the bivariate VAR with the 3-month absolute basis (ABAS3) and the effective spread (ESPR). Impulse responses are presented for the vector autoregression that pairs the 3-month adjusted absolute basis with the adjusted value-weighted effective spread on the NYSE from 1988 to 2002 (both variables are adjusted for time trends and other regularities). Monte Carlo two-standard-error bands (based on 1,000 replications) are provided along with the estimated responses.

are consistent with an interpretation that if the basis widens on a particular day, arbitrage forces on subsequent days bring an increase of either buy or sell orders, which strains liquidity. For the 6- and 9-month bases, we omit the effective spread responses because they are qualitatively similar to those for quoted spreads. We find that the impulse responses of spreads to absolute bases are a bit more persistent for the 3- and 6-month contracts (Figures 3 and 5) than

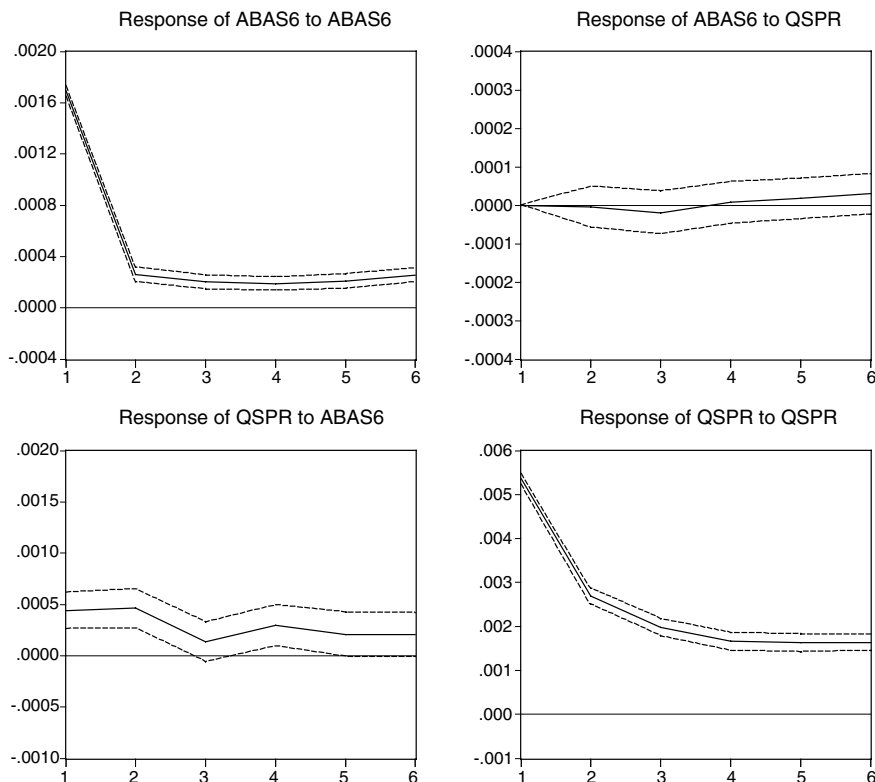
Response to Cholesky One S.D. Innovations ± 2 S.E.

Figure 5. Impulse response functions for the bivariate VAR with the 6-month absolute basis (ABAS6) and the quoted spread (QSPR). Impulse responses are presented for the vector autoregression that pairs the 6-month absolute basis with the NYSE value-weighted quoted spread from 1988 to 2002 (both variables are adjusted for time trends and other regularities). Monte Carlo two-standard-error bands (based on 1,000 replications) are provided along with the estimated responses.

for the 9-month contract (Figure 6), again suggesting more intense arbitrage activity in shorter contracts.²²

Impulse responses of the 3-month and 6-month absolute bases to spreads are not significant. Thus, even though the spread Granger-causes the shorter-term absolute bases, after accounting for the joint dynamics, including the

²² Indirect evidence that arbitrage activity follows days on which the absolute basis widens can be obtained from examining order flow. Harford and Kaul (2005) document a significant index-related component in stock order flows. Using an (imperfect) index of order flow based on Chordia et al. (2002), who, in turn, use the Lee and Ready (1991) signing algorithm, we find that the univariate correlation between current net buying activity and the lagged (signed) 3-, 6-, and 9-month bases are 0.084, 0.090, and 0.087, respectively, which are all statistically significant at the 1% level. Thus, there is evidence that net buying activity in the cash market follows days on which the futures component of the basis is high relative to the cash component; this is consistent with arbitrageurs reacting to the size of the basis.

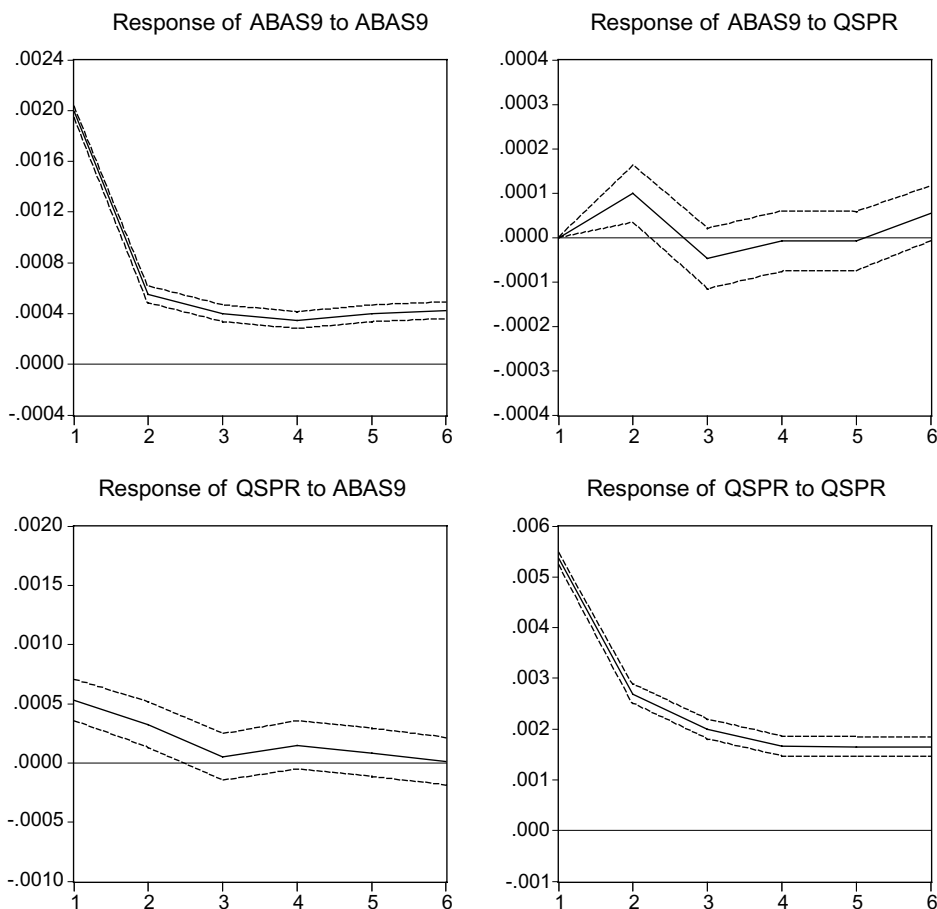
Response to Cholesky One S.D. Innovations ± 2 S.E.

Figure 6. Impulse response functions for the bivariate VAR with the 9-month absolute basis (ABAS9) and the quoted spread (QSPR). Impulse responses are presented for the vector autoregression that pairs the 9-month absolute basis with the NYSE value-weighted quoted spread from 1988 to 2002 (both variables are adjusted for time trends and other regularities). Monte Carlo two-standard-error bands (based on 1,000 replications) are provided along with the estimated responses.

persistence of the absolute basis and liquidity variables, shocks to spreads are statistically uninformative in forecasting these bases. Note, however, that for the 9-month case, the spread is indeed informative in predicting shocks to the absolute basis at the second period, (Figures 7 and 8). This is consistent with our previous interpretation of the Granger-causality results, that liquidity affects the future activities of arbitrageurs relatively more in the less liquid, longer-term contracts.

With respect to the economic significance of the IRFs, a one-standard deviation shock from the 3-month absolute basis impacts effective spreads and

aggregates to an *annualized* extra trading cost of about \$1 million for a daily round-trip trade of one million shares in the basket of NYSE-listed common stocks. Furthermore, in the case of the 9-month basis measure, for an average stock price of \$40 and a trade of one million shares, a one standard deviation shock to spreads results in an annualized cumulative divergence of \$1 million between the futures and its cash value.²³ Thus, the economic relevance of both effects appears to be material. Note that if arbitrage often involves trades outside of the quoted spread, the actual economic significance may be even higher than those we report. We briefly consider an alternative measure of liquidity in the section to follow.²⁴

V. Discussion and Robustness Checks

The first potential issue pertains to the adjustment of the bases and spreads for calendar regularities and secular trends, a process designed to remove possible spurious covariation. Common regularities in the absolute basis and spreads might or might not represent genuine causation.²⁵ A direct remedy is simply to recompute the vector autoregressions using the unadjusted series. For brevity, results using the unadjusted series are not reported, but they are qualitatively unaltered in every respect. Thus, the adjustment procedure has minimal impact on inferences.

To study robustness to alternative measures of liquidity, abridged results are hereafter reported using depth, which is positively associated with liquidity. The depth measure is calculated by averaging the posted bid and ask guaranteed share *quantities* accompanying each bid and ask price quote, then averaging over the trading day for each stock, and then value-weighting

²³ This calculation of economic significance is based on the 6-day cumulative impulse response of one variable to a one-standard deviation shock in the other. In the first case (the response of liquidity to the absolute basis), taking the total incremental trading cost per million shares traded and multiplying by the number of trading days in a year (250) yields the dollar amount reported above. In the second case, the cumulative impulse response over 6 days is multiplied by the dollar value of the trade, and then by 250, the approximate number of trading days in a year, to arrive at the reported number.

²⁴ It may be worth considering the use of futures liquidity data in addition to stock liquidity. Since there are no posted quotes on the futures market, futures liquidity is hard to estimate. Also, as the autocorrelation in futures price changes is small and not consistently negative, the Roll (1984) measure also is infeasible to implement. Since arbitrageurs have to execute trades in a basket of stocks (i.e., many stocks) simultaneously and incur liquidity costs in each individual security, aggregate cash market illiquidity should be the main impediment to arbitrage. We did include futures volume in the VAR and found causality running from the 3-month absolute basis to futures volume, and from futures volume to the 6-month basis, suggesting a joint dynamic structure between futures trading activity and the basis. These results are available upon request.

²⁵ An example of possible economic causation that the adjustment removes is the following: the mean values of the 3-, 6-, and 9-month absolute bases decreased, respectively, from 0.173 to 0.154, 0.248 to 0.191, and 0.357 to 0.278 from the pre- to the post-decimal tick size period. All of these decreases are statistically significant at the 5% level. While it is tempting to attribute these changes to a secular increase in liquidity, other events (e.g., technological innovations speeding up execution of arbitrage trades) could also have played a role.

Table VIII
Robustness Checks with Market Depth

Panels A and B present regression results for each measure of the adjusted absolute basis (ABAS_x, where *x* represents the basis horizon in months) on one lag of adjusted depth, and vice versa. The adjusted series are residuals from the regressions involving the independent variables in Tables II and III. Panel C presents pairwise Granger-causality tests between the endogenous variables. In Panel A, the coefficients are multiplied by 1,000.

Panel A: Absolute Bases as Dependent Variables and Lagged Depth as Independent Variable						
Dependent Variable	Independent Variable: Lag(Depth)					
	Coefficient		T			
ABAS3	−0.126		−6.97			
ABAS6	−0.114		−5.54			
ABAS9	−0.001		−0.32			
Panel B: Depth as Dependent Variable and Absolute Bases as Independent Variables						
Dependent Variable	Independent Variable: Lag(ABAS3)		Independent Variable: Lag(ABAS6)		Independent Variable: Lag(ABAS9)	
	Coefficient	T	Coefficient	T	Coefficient	T
DEPTH	−118.88	−8.26	−81.38	−6.36	−10.20	−1.06
Panel C: Granger-Causality Tests (Null Hypothesis: Row Variable Does Not Granger-Cause)						
	ABAS3		ABAS6		ABAS9	
ABAS3	−		−		−	32.60 (0.00)
ABAS6	−		−		−	17.34 (0.01)
ABAS9	−		−		−	12.37 (0.05)
DEPTH	23.47 (0.00)		7.29 (0.30)		8.48 (0.21)	−

across stocks. The resulting average depth measure is finally adjusted using the variables in Table IV. Panels A and B of Table VIII present regressions corresponding to Table VI that replace adjusted depth as a measure of liquidity, while Panel C reports the Granger-causality tests involving this measure.

In every instance, the regression coefficients are negative, which is reassuring, since depth is positively related to liquidity (whereas the reverse is true of spreads). The coefficients are significant, as in Table VI, for the shorter-term absolute bases. The Granger-causality results in Panel C of Table VIII indicate that depth and the 3-month absolute basis Granger-cause each other, and the 6- and 9-month absolute bases Granger-cause market depth. These results are largely consistent with Table VII, suggesting that previous

inferences are largely unaltered by the use of depth as an alternative measure of liquidity.²⁶

Fluctuations in liquidity can arise either from demand-related shifts (e.g., shocks to investors' trading needs) or supply-related ones (e.g., shifts in borrowing terms, which affect market makers' access to capital). While a detailed analysis of the causes of daily liquidity fluctuations warrants a separate paper, previous literature suggests that the most important candidates for common determinants of liquidity and the absolute basis are return volatility as well as the signed return (see, e.g., Benston and Hagerman (1974), MacKinlay and Ramaswamy (1988), and Hasbrouck, (1991)). As such, it is of interest to consider the extent to which our results are driven by return and volatility dynamics.

To address this issue, we perform a robustness check by including six lags of return and index volatility in the VAR system.²⁷ Again, while the estimates from this exercise are not reported for brevity, our conclusions on commonality between the absolute basis and liquidity are largely unaltered. Conclusions about all three aspects of the VAR, namely, innovation correlations, Granger-causality results, and the impulse response functions, remain unchanged. Thus, volatility and returns alone do not capture the common dynamics of the absolute basis and liquidity. This is consistent with the notion that changes in liquidity-related factors *other* than returns and volatility, such as shifts in market makers' ability to supply liquidity, and shifts in investors' liquidity needs, play an important role in the effectiveness of arbitrage activity.

Note that we have reported the results of VARs where liquidity measures are paired with a basis measure. This allows us to avoid issues of multicollinearity affecting the inferences. For example, testing for whether quoted spreads Granger-cause absolute bases in the presence of the effective spread in the equation for the absolute basis may lead to spurious conclusions. Nonetheless, to consider the robustness of our results to alternative specifications, we also estimated a five-equation VAR, which included the three bases and the two liquidity measures. The results from this estimation did not differ substantively from the one reported (though in the presence of the effective spreads, the quoted spreads became less significant), and are available upon request.

Thus far, the NYSE composite index futures basis has been the focus of inquiry, in part because the influence of illiquidity on the basis is more likely to be evident in a cash basket comprising a large number of stocks, some of which might not be all that liquid. It is potentially instructive, however, to consider whether similar results obtain with more liquid index futures contracts. To

²⁶ As per the Schwarz criterion, six lags are used in the depth VARs. The impulse response functions are not presented for brevity but are consistent with the Granger-causality results. Since spreads and depth are related, there is a possible multicollinearity problem, but the results for depth turn out to be largely insensitive to whether or not spreads are included in the VAR. (Spreads are not included in the reported VARs.)

²⁷ Index return and index volatility are obtained, respectively, as the residual and absolute value of the residual from a regression of the index return on the past 12 lagged returns and four dummies for days of the week (see Schwert (1990), Jones, Kaul, and Lipson (1994), and Chan and Fong (2000)).

Table IX
Robustness Checks for the S&P 500 Futures Contract

Panels A and B present regression results for each measure of the 3-month adjusted absolute basis (ABASE) on one lag of quoted and effective spreads, and vice versa, for the S&P 500 index futures contract and the cash index. The adjusted series are residuals from regressions such as those in Tables III and IV spanning the period 1993 to 2002. Panel C presents pairwise Granger-causality tests. In Panel A, the coefficients are multiplied by 1,000.

Panel A: Absolute Bases as Dependent Variables				
Dependent Variable	Independent Variable: Lag(QSPR)		Independent Variable: Lag(ESPR)	
	Coefficient	<i>T</i>	Coefficient	<i>T</i>
ABAS3	1.125	4.24	1.738	4.85
Panel B: Liquidity Measures as Dependent Variables				
Dependent Variable	Independent Variable: Lag(ABAS3)			
	Coefficient			<i>T</i>
QSPR	0.646			6.53
ESPR	0.605			8.27
Panel C: Granger-Causality Tests (Null Hypothesis: Row Variable Does Not Granger-Cause Column Variable)				
	ABAS3	QSPR	ESPR	
ABAS3	—	36.76 (0.00)	17.31 (0.01)	
QSPR	4.78 (0.57)	—	—	
ESPR	13.82 (0.03)	—	—	

explore this issue, we first calculated the cash-futures basis for the S&P 500 index futures contract for the period 1988 to 2002. The new liquidity index uses only NYSE stocks in the S&P 500. The inclusion criteria were the same as those described in Section I, with the added requirement that a stock be present in the S&P 500 index at the beginning of the year.

Results for the 3-month absolute basis are presented in Table IX. They are largely consistent with earlier ones. One-day lags of illiquidity measures are significantly related to the absolute basis, and vice versa. In addition, the absolute basis Granger-causes quoted spreads and there is two-way causality between effective spreads and the absolute basis. Results for the longer-term bases are not presented for brevity, but are largely consistent with the analogous ones reported previously for the NYSE composite futures contracts.

Since late January 1993, SPIDERS (Standard and Poor's Depositary Receipts), which trade the S&P 500 basket in a single transaction, have been available on the American Stock Exchange. If illiquidity is a bigger problem when arbitrage positions involve multiple transactions, then a futures-cash

Table X
**Robustness Checks for the S&P 500 Futures Contract and SPIDERS
as the Cash Contract**

Panels A and B present regression results for each measure of the 3-month adjusted absolute basis (ABAS3) on one lag of quoted and effective spreads, and vice versa, using the S&P 500 index futures contract and the S&P 500 SPIDER as the cash instrument. The adjusted series are residuals from regressions such as those in Tables III and IV spanning the period 1993 to 2002. Panel C presents pairwise Granger-causality tests.

Panel A: Absolute Basis as the Dependent Variable				
Dependent Variable	Independent Variable: Lag(QSPR)		Independent Variable: Lag(ESPR)	
	Coefficient	<i>T</i>	Coefficient	<i>T</i>
ABAS3	0.056	2.03	0.003	0.46
Panel B: Liquidity Measures as Dependent Variables				
Dependent Variable	Independent Variable: Lag(ABAS3)			
	Coefficient		<i>T</i>	
QSPR	0.024		1.63	
ESPR	0.021		0.34	
Panel C: Granger-Causality Tests (Null Hypothesis: Row Variable Does Not Granger-Cause Column Variable)				
	ABAS3	QSPR	ESPR	
ABAS3	—	2.28 (0.32)	0.165 (0.92)	
QSPR	12.15 (0.00)	—	—	
ESPR	0.237 (0.89)	—	—	

basis where the SPIDER is the cash instrument should exhibit fewer illiquidity effects. We investigate this possibility by constructing the basis between the SPIDER and the S&P 500 futures contract from January 1993 to December 2002. Daily average quoted and effective spreads for SPIDERS are also computed over the same period.

Results for the 3-month basis and liquidity are presented in Table X. As expected, the results are statistically weaker than those in Table IX. While all point estimates in the regressions involving one lag of the variables are positive, only the lagged quoted spread is significant. Furthermore, Granger causality runs only from the quoted spread to the absolute basis (this is true for all three absolute bases, though again, results for the longer-term bases are omitted for conciseness). The relatively low cost of trading SPIDERS evidently renders arbitrage more effective.

Until now, daily average quoted and effective spreads have served as illiquidity measures. They should be good illiquidity indicators when arbitrage trades

Table XI
Results for a Price Impact Measure of Illiquidity

Panel A presents regression results for each measure of the 3-month adjusted absolute basis (ABAS3) on one lag of PRIM (a price impact measure of illiquidity), and vice versa. PRIM is the average effective spread for orders greater than 500 shares. The adjusted series are residuals from regressions such as those in Tables 3 and 4 spanning the period 1993 to 2002. Panel B presents pairwise Granger-causality tests. In Panel A, the coefficients are multiplied by 1,000.

Panel A: Regressions				
Dependent Variable	Independent Variable: Lag(PRIM)		Independent Variable: Lag(ABAS3)	
	Coefficient	<i>T</i>	Coefficient	<i>T</i>
ABAS3	0.139	1.45	–	–
PRIM	–	–	1.126	2.71
Panel B: Granger-Causality Tests (Null Hypothesis: Row Variable Does Not Granger-Cause Column Variable)				
	ABAS3		PRIM	
ABAS3	–		27.45 (0.00)	
PRIM	12.78 (0.05)		–	

are small enough to be within the quoted depth.²⁸ Arbitrage trades may, however, sometimes consist of larger order sizes, so it might be worth considering liquidity measures that are sensitive to the price impact of large trades. Many stocks in the NYSE index are infrequently traded, and our study uses a daily horizon, so a daily measure based on intraday regressions (e.g., Glosten and Harris (1988)) presents problems. We propose instead to use the daily average effective spread associated with large orders. Following Barclay and Warner (1993), who classify orders less than 500 shares as small,²⁹ we average 500 shares and larger effective spreads for each stock on a daily basis, using TAQ data for the 1993 to 2002 period, and then value-weight this average across NYSE stocks.

Results using this modified illiquidity measure and the 3-month absolute basis are reported in Table XI. We see that the measure is positively and significantly related to one lag of the absolute basis, while there is two-way Granger-causality between the basis and the measure.³⁰ From unreported VARs, we find

²⁸ Neal (1996, p. 547) points out that average buy and sell orders by index arbitrageurs average a modest 653 and 1,385 shares, respectively, which are within the average quoted depth on the NYSE (Chordia, Roll, and Subrahmanyam (2001)).

²⁹ This measure has been discussed by Bessembinder (2003), Jones and Lipson (2001), and Vihj (1990).

³⁰ The *p*-value for Granger causality running from the price impact measure to the 3-month absolute basis is 0.047 when carried up to three decimal places.

that this causality is confined to the short-term basis, unlike in the case of our earlier illiquidity measures, which possibly implies that arbitrage activities in the relatively less active longer-term contracts involve small orders to prevent trading costs from becoming too large. Overall, the analysis once more confirms the joint dynamic relation between illiquidity and deviations from no-arbitrage relations.

Arbitrage positions often require financing and thus may depend on short-term interest rates. Furthermore, liquidity may also depend on dealer financing costs (Demsetz (1968)). For example, by reducing the cost of margin trading and decreasing the cost of financing inventory, a decrease in short rates could stimulate trading activity and increase market liquidity. To ascertain whether previous results are proxying for this common determinant of trading costs, and to gain a greater understanding of the economics of arbitrage, we use two measures of short-term interest rates as exogenous variables in the VAR system. The first measure is the Federal Funds rate, which is related to day-to-day financing of inventory or arbitrage positions.³¹ The second is the constant-maturity (6-month) Treasury Bill rate, which is related to the financing of longer-term positions. Prior to their usage in the regressions, these variables are adjusted for weekly and monthly seasonals, holidays, and linear and quadratic trends. We find that inclusion of the short rates does not change the qualitative conclusions on Granger causality for either the NYSE composite or the S&P 500 futures-cash bases, and also find that the Federal Funds rate bears a positive relation to the short-term absolute basis, and that this relation is significant in the case of the latter index (detailed results are available upon request). Overall, this suggests a role for interest rates as proxies for financing costs, and also indicates that previously reported results cannot be attributed to an exogenous interest rate influence driving both the basis and liquidity. Doubtless, many phenomena, including news arrivals that cause changes in agents' expectations, and unexpected wealth shocks, drive the dynamics of liquidity, and these drivers warrant separate research.

Our final robustness check involves the effects of possible nonsynchronous trading in the constituent stocks of the index. The NYSE composite index is value-weighted, so the impact of nonsynchronous trading at a daily horizon should be fairly small; the first order return autocorrelation for the NYSE composite index is a modest 0.045, yet a potential concern is that wider bases may be associated with greater nonsynchronous trading (and less liquidity).³² To investigate this possibility, we regressed index returns on lagged index returns *and* the lagged adjusted absolute basis and found no evidence that serial dependence is greater when the basis is wider.

A related issue is that high absolute return days may be accompanied by high spreads, high nonsynchronous trading and a wider basis as the futures price adjusts faster than the cash index to new information; but this possibility

³¹ Interest rates are obtained from <http://www.federalreserve.gov/releases/h15/data.htm>.

³² The first-order daily return autocorrelation for the S&P 500 index is an insignificant 0.005, suggesting that nonsynchronous trading is not an issue for this index.

conflicts with our forecasting results, which are unaltered after controlling for volatility.

Nonetheless, to further address any possible influence of nonsynchronous trading, we adopt the approach of Jokivuolle (1995), who devises a method for estimating the true value of an index when some of its constituents are subject to stale pricing. He shows that the log of the true index value can be represented as the permanent component of a Beveridge and Nelson (1981) decomposition of the series of log index first differences. Jokivuolle uses the Russell 2000 as an empirical example, but this index includes many small stocks so the nonsynchronous trading problem is more severe than in our case; this is indicated by his first-order autocorrelation of 27%, compared to ours of about 5%. His technique³³ reduces the autocorrelation of the “true” NYSE composite index returns to 0.006. Details appear in Appendix B.

Using the Jokivuolle “true” NYSE composite index to compute the bases, Figure 7 shows the response of quoted spreads to the 3-month absolute basis, and the response of the 9-month basis to quoted spreads. As can be seen, the impulse responses are very similar to their respective counterparts in Figures 3 and 6. Other contracts are not presented for brevity, but they also are qualitatively unaltered when using the “true” index. Nonsynchronous trading does not have a material impact on our results.

VI. Conclusions

Because liquid markets facilitate arbitrage trades, relative pricing in the cash and futures markets should be more efficient when liquidity is high. On the other hand, arbitrage trades themselves could reduce liquidity by creating order imbalances. To study these ideas, we use three futures-cash basis series involving contracts maturing within 3, 6, and 9 months, along with two measures of liquidity, quoted and effective spreads. We find that the dynamics of the absolute futures-cash basis and liquidity are jointly determined.

The empirical findings include the following: (1) The speed of mean-reversion of the basis (to zero) over a futures contract’s lifetime is positively related to liquidity; (2) there is two-way Granger causality between the 3-month absolute basis and liquidity, as measured by effective spreads; (3) impulse response functions reveal that shocks to the absolute bases are significantly informative in predicting future shifts in spreads; (4) contemporaneous innovations to the absolute basis and spreads are positively correlated; (5) shocks to spreads are more informative in forecasting shifts in the 9-month absolute basis than in the shorter-term bases, suggesting that liquidity affects arbitrageurs more in the relatively less actively traded longer-term futures contracts.

All these results are preserved after controlling for short-term interest rates, suggesting that the results cannot be attributed to arbitrage financing costs.

³³ Jokivuolle (1995) uses an MA(1) process to model the first differences of the log index; the same choice is appropriate here as well, since, as in his paper, the autocorrelations beyond the first lag (up to a week of “meaningful” lags) are quite small (0.03 or less) in magnitude.

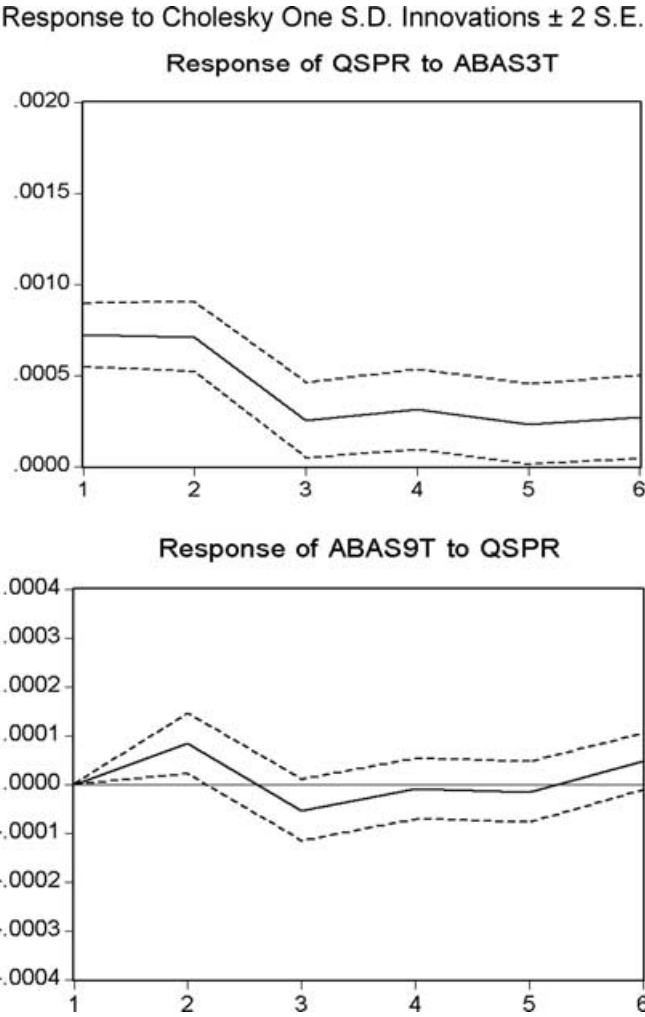


Figure 7. Impulse response functions for the bivariate VARs with the 3- and 9-month absolute bases adjusted for nonsynchronous trading (ABAS3T and ABAS9T, respectively) and the quoted spread (QSPR). Impulse responses are presented for the vector autoregression that pairs the 3- and 9-month absolute bases, corrected for nonsynchronous trading, with the NYSE value-weighted quoted spread from 1988 to 2002 (both variables are adjusted for time trends and other regularities). Monte Carlo two-standard-error bands (based on 1,000 replications) are provided along with the estimated responses.

Overall, the results are consistent with the notion that deviations from no-arbitrage relations forecast and, in turn, are forecasted by liquidity. If the degree to which markets satisfy the law of one price is taken to be a measure of the market's efficiency, then the results suggest that liquidity plays a significant role in moving markets toward an efficient outcome. In the reverse direction, the results suggest that deviations from the law of one price on a given day

can help in predicting market liquidity on subsequent days, which is consistent with arbitrageurs affecting liquidity by their trading. Hence, the absolute basis may provide information to both retail and institutional investors that can be valuable in the forecasting and control of trading costs.

A possible empirical extension of this analysis would consider whether the ability of futures-cash bases to forecast liquidity and vice versa holds in other markets such as fixed-income and foreign exchange. It would also seem desirable to consider the basis/liquidity relation prior to days of news announcements (when the market might be particularly illiquid because of asymmetric information stemming from news leakage). Finally, it may be worthwhile to consider technological innovations in financial markets (such as the development of electronic communication networks). How such developments affect the basis by way of the liquidity channel would appear to be an interesting area for further research.

Appendix A: Estimation of the Mean Reversion Parameter in Table II

The basis is given by

$$dB(t) = -\frac{\mu B}{\tau} dt + \gamma dz. \quad (\text{A1})$$

Standard arguments imply that the value of $B(t)$ at a point in time can be written as

$$B(t) = \gamma(T-t)^\mu B \left[\frac{(T-t)^{1-2\mu}}{2\mu-1} \right], \quad (\text{A2})$$

where dz is a standard Brownian motion.

The log likelihood function of the parameters μ and γ can then be written as

$$\ln L(\mu, \gamma) = -\frac{T}{2} \ln 2\pi - \sum_{t=1}^T \ln \sigma_t - \frac{1}{2} \sum_{t=1}^T \frac{u_t^2}{\sigma_t^2}, \quad (\text{A3})$$

where

$$u_t \equiv B(t+1) - \left(1 - \frac{1}{T-1}\right)^\mu B(t), \quad (\text{A4})$$

and

$$\sigma_t^2 \equiv \frac{\gamma^2(T-t-1)}{2\mu-1} \left[1 - \left(1 - \frac{1}{T-t}\right)^{2\mu-1} \right]. \quad (\text{A5})$$

The parameters can be estimated by maximizing the above log-likelihood function. The estimate of the mean-reversion parameter μ for each contract can be related to the average level of liquidity during the contract's lifetime.

Appendix B: Adjustment of the Stock Index to Account for Nonsynchronous Trading

To investigate a possible influence of nonsynchronous trading on our results, we adopt a procedure devised by Jokivuolle (1995), who shows that a log index corrected for nonsynchronous trading is equivalent to the Beveridge and Nelson (1981) permanent component of a fitted ARIMA process. As an empirical illustration, Jokivuolle uses the Russell 2000 index, which includes many infrequently traded small firms. He notes that autocorrelations in this index's returns (the first differences of the log index levels), are significant only at the first daily lag, which implies that a first-order moving average process is adequate to describe the index returns. Our index, the NYSE composite, also has significant autocorrelation only at the first daily lag, so we adopt his illustrative method.

Specifically, let I_t be the NYSE composite index on day t and define $R_t = \ln(I_t/I_{t-1})$ as the log return. An MA(1) process for R_t implies

$$R_t = R_e + \theta \varepsilon_{t-1} + \varepsilon_t, \quad (\text{B1})$$

where R_e is the expected return, θ is a moving average parameter, and the ε 's are independent and identically distributed disturbances. Jokivuolle shows that the Beveridge and Nelson-corrected log index for day t is given by

$$\ln(I_t) + \theta \varepsilon_t. \quad (\text{B2})$$

The parameter θ can be estimated from the first-order autocorrelation coefficient of returns, $\rho = \text{Cov}(R_t, R_{t-1})/\text{Var}(R) = \theta/(\theta^2 + 1)$. When θ is small, its value is close to the autocorrelation coefficient itself. Nonetheless, we computed an exact estimate by taking the negative root of the equation $\rho(\theta^2 + 1) + \theta = 0$. Using all daily observations in the sample, we estimate θ to be 0.04531.

To obtain a time series for ε_t , the moving average process must be inverted. Recursive substitution of lagged values; that is, $\varepsilon_t = R_t - R_e - \theta[R_{t-1} - R_e - \theta(R_{t-2} - R_e - \theta \varepsilon_{t-3})]$ eventually gives the correction term

$$\begin{aligned} \theta \varepsilon_t &= \theta(R_t - R_e) - \theta^2(R_{t-1} - R_e) + \theta^3(R_{t-2} - R_e) - \theta^4(R_{t-3} - R_e) + \cdots \\ &= \theta R_t - \theta^2 R_{t-1} + \theta^3 R_{t-2} - \theta^4 R_{t-3} + \cdots - R_e \theta / (\theta + 1). \end{aligned} \quad (\text{B3})$$

Since θ is small, the powered terms decline rapidly and are essentially immaterial after a few lags. We stopped adding terms after four lags as additional terms would have mattered only in the 11th or 12th decimal place. For the final term above, the sample mean return was substituted for R_e .

The resulting corrected NYSE index returns have a first-order autocorrelation of 0.00597, with an insignificant t -statistic of 0.366. This contrasts with the observed index, whose returns have a first-order autocorrelation of 0.0452 and a t -statistic of 2.78. The Jokivuolle (1995) procedure does indeed appear to work well in correcting the index for nonsynchronous trading. As mentioned in Section V, however, our results are materially unaltered when the corrected index is used in the computation of the basis.

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