Commodity Liquidity Measurement and Transaction Costs

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We examine the performance of liquidity proxies in commodities. The Amihud measure has the largest correlation with liquidity benchmarks. Amivest and Effective Tick measures also perform well. These proxies are useful for studies of commodity liquidity over a long time period and those that lack access to high-frequency data. We use various aspects of transaction costs, such as spread, depth, immediacy, and resiliency, to give insight into the costs of different execution approaches. Transaction costs increase with volatility and exhibit mean reversion. Splitting trades over one hour can reduce trading costs by two-thirds compared to an immediate execution. (*JEL* G11, G12, G13)

Liquidity plays a crucial role in many empirical studies, so it is important that researchers measure it accurately. The purposes of this article are two-fold: (1) to identify the liquidity proxies that best capture the costs of trading commodities; and (2) to document actual transaction costs of commodities for different trade sizes and order execution approaches. Numerous liquidity proxies based on daily data have been developed in the last few decades to assist researchers in studies that require liquidity measures over a long period of time, where high-frequency data are unavailable, or where computationally intensive liquidity measurement using high-frequency data is simply not warranted. The correlation between these liquidity proxies and equity market

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liquidity benchmarks has been well established (e.g., Goyenko, Holden, and Trzcinka 2009), but their effectiveness for commodities remains an open question. Locke and Venkatesh (1997) and Ferguson and Mann (2001) show that the Roll (1984) measure is a poor proxy for commodity liquidity. However, the effectiveness of the many newer proxies has not been documented despite commodities emerging as an increasingly popular and important asset class.[1]

The scale of a liquidity proxy is just as important as the proxy's correlation with true transaction costs in numerous applications (e.g., Goyenko, Holden, and Trzcinka 2009). Many popular liquidity proxies have a unit of measurement that is quite different from the underlying transaction costs. This may not be important for applications like asset pricing research, but it does reduce their worth to researchers who study trading strategies and asset allocation, and to market participants such as active traders who require precise measures of transaction cost levels. Actual transaction costs in equity and bond markets are well documented (e.g., Bessembinder and Kaufman 1997; Edwards, Harris, and Piwowar 2007). However, much less is known about commodity trading costs.[2] We present commodity transaction costs from different angles, for different trade sizes, and over a range of order execution scenarios. Trading commodity futures also incur clearing, exchange, and brokerage fees, which are relatively low.[3]

We study the twenty-four commodities that comprise the S&P Goldman Sachs Commodity Index (S&P GSCI). These commodities include agricultural, energy, industrial metal, livestock, and precious metals. The commodity futures data we use are from the Thomson Reuters Tick History (TRTH) database.[4] These data contain tick pit and electronic trading data for all the major commodities, which allows us to calculate effective spreads, quoted spreads, and price-impact benchmarks to represent actual transaction costs. We also use TRTH order book data, which include the bid and ask prices and depth for up to ten levels, to calculate transaction costs for alternative scenarios. The performance of the seventeen low-frequency liquidity proxies is assessed using daily data from Thomson Reuters Datastream.

The Amihud (2002) measure has the largest correlation with each of the three liquidity benchmarks. The Amivest (Amihud, Mendelson, and Lauterbach 1997) and Effective Tick (Holden 2009) measures are the next best proxies. We suggest that future research focusing on topics such as the role liquidity plays in commodity asset pricing should therefore use the Amihud measure in

[1] For instance, long-only commodity index assets grew more than twenty-fold in the ten years to 2007. See Figure 21.1 in Dunsby et al. (2008). Hereafter, all currency amounts are in U.S. dollars.

[2] Locke and Venkatesh (1997) and Ferguson and Mann (2001) are among the few papers that document transaction commodity transaction costs. They study five agricultural commodities over 126 days in 1992.

[3] Fees vary across brokers, with total costs as low as $2.06 per trade (see http://www.generictrade.com/commissions/).

[4] The TRTH data are provided by the Securities Industry Research Centre of Asia-Pacific (SIRCA), http://www.sirca.org.au.

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their low-frequency analysis if they are limited to one proxy. More ideally, such research should use the Amihud, Amivest, and Effective Tick measures together. If a researcher lacks dollar volume data, then Effective Tick should be used.

Following Goyenko, Holden, and Trzcinka (2009), we calculate the root mean squared errors between the liquidity proxies and liquidity benchmarks to determine if the scale of the proxy is consistent with the benchmark scale. Some proxies, such as the Amihud measure, have a unit of measurement that is clearly different from the benchmarks; so, like Goyenko, Holden, and Trzcinka (2009), we exclude these from the root mean squared error analysis. We find that all liquidity proxies have a statistically significantly different scale from the transaction cost benchmarks. The root mean squared error of the spread proxies is larger than the size of actual spread, while the root mean squared error of price impact proxies is almost half of the actual price impact. As this bias warrants careful treatment when using the level of liquidity proxies, we shed some light on the level of actual trading costs by reporting the different aspects of transaction costs, such as spread, depth, immediacy, and resiliency. These provide insight into the actual trading costs for different trade sizes under different scenarios, such as when investors require immediate execution and when they are prepared to wait for different lengths of time to complete their trades.

Spread, the cost of trading at the best bid or ask price, is the most common transaction cost benchmark. Researchers who calculate spread using high-frequency equity data include Goyenko, Holden, and Trzcinka (2009), Hasbrouck (2009), Fong, Holden, and Trzcinka (2010), and Corwin and Schultz (2011). Depth is also highly important to investors, for it is the amount that can be transacted at a given price. The spread cost is pertinent only for the amount traded at the best bid or ask quote. A trader who requires immediate execution of a large order may have only the first portion filled at the best bid or ask quote. The second portion will be filled at the second best bid or ask price in the order book, and so on. The difference between the best and second best prices and the amount that can be transacted at each level of the book will both influence the transaction costs incurred by the investor. Resiliency is another aspect of transaction costs. Kempf, Mayston, and Yadav (2009) note that resiliency refers to the speed at which spread and depth recover following large trades. This is critically important to investors who wish to minimize transaction costs by splitting large trades into smaller components to execute over time.[5]

We find that commodity markets are resilient. Over 70% of depth is restored five minutes after large trades, and liquidity returns to pre-trade levels after thirty to sixty minutes. Patient investors experience a meaningful reduction in transaction costs if they split their trades by executing only the portion that is tradable at the first level of the order book and then wait five minutes for

[5] Our depth, immediacy, and resiliency analysis is based on order book data, so it will understate liquidity to the extent of liquidity in the open outcry segment of the market. It also does not account for hidden limit orders.

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liquidity to be restored before executing the next portion. The average transaction cost (measured as the relative difference between the midpoint of the best bid and ask quotes at the time the first portion of the trade is transacted and the weighted average execution price) for a $1,000,000 trade for an investor prepared to wait 60 minutes for complete execution ranges from 6.5 to 8.6 basis points.[6] These are considerably lower than the average 25.8 basis points that impatient traders pay for immediate execution of a $1,000,000 trade. Moreover, there are times when relatively large trades cannot be executed immediately. For instance, a $1,000,000 trade, on average, cannot be completed 28% of the time due to insufficient liquidity in the order book.

There are noticeable differences in transaction costs across commodities. Energy and precious metal commodity families consistently have lower average trading costs than livestock and agricultural commodities. There is also variation within commodity families. For instance, soybeans have relatively low transaction costs. The trading costs of all commodities increase with return volatility, but this relationship varies across commodity families. Energy returns are considerably more volatile than the returns of other commodities, but energy trading costs are less sensitive to return volatility than other commodity families, such as the livestock family.

These transaction cost findings should be of interest to a number of parties. A recent commodity momentum paper by Miffre and Rallis (2007, p. 1885) could not "draw final inferences on the magnitude of the net momentum profits." Future trading rule studies can use our transaction cost results to calculate net profits, if any, for a range of trade sizes. Those wishing to diversify portfolios using commodities based on the findings of Gorton and Rouwenhorst (2006) can use our trading cost findings to estimate diversification benefits net of transaction costs. These costs may be a key input, as De Roon, Nijman, and Werker (2001) show that apparent diversification advantages can disappear when transaction costs are accounted for in equity markets. Perold and Schulman (1988) note that transaction costs are an important input in the hedging process. Hedgers can make use of our numbers in their cost-benefit analysis.

Our transaction cost results are also relevant to regulators. In responding to a request from the Commodity Futures Trading Commission (CFTC) for comment on the proposed registration of the U.S. Futures Exchange, the Federal Trade Commission (FTC) made extensive reference to the cost of executing trades. The fact that it believed these would decrease appears to have been a significant factor behind its recommendation to allow the U.S. Futures Exchange to gain registration.[7]

Exchanges can also use our findings. Harris (2003) suggests that transaction cost levels are an important marketing tool for exchanges, as they compete for

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6 All transaction cost analysis excludes industrial metals, as we do not have trade values for these commodities.

7 http://www.cftc.gov/files/submissions/comments/comdcm037ftc.pdf.

business. Competition for commodity offerings is increasing by the day. China has established the Zhengzhou Commodity Exchange,[8] and the Singapore Exchange[9] continues to expand its commodity contract offerings. Furthermore, transaction costs are directly related to market efficiency, which impacts all market participants (e.g., Chordia, Roll, Subrahmanyam 2008). Commodity researchers who study arbitrage activity or commodities from other perspectives, such as the costs and benefits of hedging, may also wish to use our detailed transaction cost estimates.[10]

The rest of this article is organized as follows: Section 1 describes the data sources. Section 2 presents the liquidity measures. Section 3 contains the liquidity proxy results, and Section 4 discusses the transaction costs across a number of dimensions and documents the benefits of trade splitting. Section 5 concludes.

1. Data

We use commodity futures rather than spot data for several reasons. First, further data receive the most coverage in the media and are used to construct the major commodity indices. Second, Bernanke (2008) notes that commodity futures prices contain valuable information for policymakers. Third, high-frequency tick data for commodity futures are more readily available. Our sample consists of the twenty-four commodities that comprise the S&P Goldman Sachs Commodity Index (S&P GSCI). The commodities we study include six energy commodities (West Texas crude oil, Brent crude oil, RBOB[11] gasoline, heating oil, gasoil, and natural gas), eight agricultural commodities (wheat, red wheat, corn, soybeans, cotton, sugar, coffee, and cocoa), three livestock commodities (live cattle, feeder cattle, and lean hogs), five industrial metals (aluminum, copper, nickel, zinc, and lead), and two precious metals (gold and silver).[12]

Some commodities trade on multiple exchanges, so we focus on data from the primary exchange, based on S&P GSCI information and Dunsby et al. (2008). The red wheat data are from the Kansas Board of Trade (KBT); the wheat, corn, and soybean data are from the Chicago Board of Trade (CBOT); the coffee, sugar, cocoa, cotton, Brent crude oil, and gasoil data come from the Intercontinental Exchange (ICE); the live cattle, feeder cattle, and lean hog data are from the Chicago Mercantile Exchange (CME); the West Texas crude oil, RBOB gasoline, and heating oil data are from the New York Mercantile Exchange (NYMEX); the gold and silver data are from COMEX, a division

8 http://english.czce.com.cn/.

9 http://www.sgx.com/wps/portal/marketplace/mp-en/products/commodities.

10 http://www.cftc.gov/files/submissions/comments/comdcm037ftc.pdf.

11 RBOB stands for "reformulated blend stock for oxygenate blending."

12 http://www.standardandpoors.com/indices/sp-gsci/en/us/?indexId=spgscirg–usd—-sp——.

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of the New York Mercantile Exchange;[13] and the industrial metal data for aluminum, copper, lead, nickel, and zinc are from the London Metals Exchange (LME).[14]

We obtain tick data from the Thomson Reuters Tick History (TRTH) via the Securities Industry Research Centre of Asia-Pacific (SIRCA). These data are sourced from exchanges via the Reuters Integrated Data Network, whose equity data are used by Fong, Holden, and Trzcinka (2010). According to these authors, other major subscribers, who take advantage of the TRTH's "millisecond-time-stamp tick data," include "central banks, investment banks, hedge funds, brokerages, and regulators" (e.g., Fong, Holden, and Trzcinka 2010, p. 17). More detail on the TRTH database is available at the Thomson Reuters website.[15]

Our quote and transaction data cover both open-outcry and electronic trading. We source data for all individual contracts and then construct continuous series of the most actively traded contracts. We follow De Ville de Goyet, Dhaene, and Sercu (2008) and replace a contract that expires in a given month m with the next nearest-to-maturity contract on the last day of the previous month $m-1$. The TRTH database began in 1996, so this is the starting point for fifteen commodities. Data for the remaining commodities became available at various points after 1996.[16] The sample period finishes at the end of August 2009. In total, we have over eighty-eight million trade observations across the twenty-four commodities.

We clean the data using a technique inspired by Brownlees and Gallo (2006) to ensure that data errors are not driving the results. We begin by calculating the α-trimmed sample mean and standard deviation for each high-frequency liquidity measure. We set α at 5%, which means the top and bottom 2.5% observations are excluded from the trimmed mean and standard deviation calculations.[17] We then remove observations that are outside the trimmed mean $+/-$ three standard deviations.

We also source order book data for the eleven commodities where they are available for the month of August 2009 from TRTH. These data include the bid and ask quotes and depth for up to ten levels. The order book is updated every time an order is entered or removed or a trade is completed. We follow Kempf, Mayston, and Yadav (2009) and record snapshots of the order book at five-minute intervals.

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13 Prior to its merger with the NYMEX, COMEX was known as the Commodity Exchange Inc.

14 The CME, CBOT, COMEX, and NYMEX are now all part of the CME group, but they have retained their individual identities. See http://www.cmegroup.com/company/history/timeline-of-achievements.html.

15 See http://thomsonreuters.com/products_services/financial/financial_products/quantitave_research_trading/tick_history.

16 This appears to be due to the patchy reporting of pit bid-ask quotes, trade prices, and volumes in electronic format for some commodities in the 1990s.

17 Brownlees and Gallo (2006) use an α of 10% in their equity market paper, noting that α is dependent on how dirty the data are. However, we follow Mancini, Ranaldo, and Wrampelmeyer (2009) and use an α of 5%.

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We use daily commodity data from Thomson Reuters Datastream. We start with all commodity contracts and form a continuous series of daily data that is aligned with each of the intra-day continuous series. We use the daily settlement price and daily high and low prices. The procedure for determining the settlement price varies across commodities, but it generally involves determining the weighted average price during a "closing range" period.[18] The fact that data providers, such as Thomson Reuters Datastream, report the official settlement price, which is not the actual close price, does not pose problems for our results. We simply use the price that most commodity researchers will use in their analysis. However, as a robustness check, we construct end-of-day series based on the last trade price each day using the TRTH high-frequency data and recalculate our results for low-frequency spread measures. The results are qualitatively identical. We also obtain daily data for the number of contracts traded so we can calculate low-frequency price-impact liquidity proxies. We convert the number of contracts traded to a dollar volume variable by multiplying the number of contracts traded by the contract size and then multiplying this by the settlement price.

2. Liquidity Measures

This section presents our high-frequency benchmarks and low-frequency proxies and describes the method used to determine which of the low-frequency proxies perform best. The method is consistent with papers that measure the ability of liquidity proxies to measure liquidity in stock markets, such as Goyenko, Holden, and Trzcinka (2009), Hasbrouck (2009), and Corwin and Schultz (2011). We form monthly observations of each high-frequency liquidity benchmark and low-frequency liquidity proxy and then measure the correlation and the difference between level of liquidity proxies and their benchmarks. We conduct this analysis separately for each commodity series, which allows us to determine if different proxies perform better in different commodities.

2.1 High-frequency benchmarks

We use three well-established liquidity benchmarks in the literature (e.g., Bessembinder and Kaufman 1997). Of the papers examining the effectiveness of liquidity proxies, Goyenko, Holden, and Trzcinka (2009) use effective spread and price impact, while Fong, Holden, and Trzcinka (2010) and Corwin and Schultz (2011) also use the quoted spread. The first benchmark is the effective spread. We calculate this for each commodity as

$$\text{Effective Spread} = 2 \cdot |\ln(P_k) - \ln(M_k)|, \tag{1}$$

[18] See http://www.cmegroup.com/market-data/files/CME_Group_Settlement_Procedures.pdf. We thank Hank Bessembinder for bringing this to our attention.

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where P_k and M_k are the price of the k^{th} trade and the midpoint of the prevailing bid and ask quote at the time of the k^{th} trade, respectively. Daily effective spread benchmarks are calculated as the average of the intra-day effective spread observations. The daily observations are then averaged to form monthly effective spreads.[19]

The second spread benchmark is the quoted spread, measured for each quote observation as

$$\text{Quoted Spread} = (A_k - B_k)/M_k, \tag{2}$$

where A_k, B_k, and M_k are the ask price, bid price, and midpoint of these two prices, respectively. Monthly benchmarks are calculated using the method discussed for effective spreads.

Following Goyenko, Holden, and Trzcinka (2009), the third benchmark is the five-minute price impact, which is measured as

$$\text{Price Impact} = \begin{cases} 2 \cdot (\ln (M_{k+5mins}) - \ln(M_k)) \text{ when the } k^{th} \text{ trade is a buy} \\ 2 \cdot (\ln (M_k) - \ln(M_{k+5mins})) \text{ when the } k^{th} \text{ trade is a sell,} \end{cases} \tag{3}$$

where $M_{k+5mins}$ is the midpoint five minutes after the k^{th} trade and M_k is the midpoint at the time of the k^{th} trade. We also require that a midpoint exist before ten minutes has elapsed for an observation to be included in our sample. We classify a trade executed above (below) the most recent mid-quote as a buy (sell), and use a tick rule as a tiebreaker for mid-quote trades (Lee and Ready 1991). Monthly benchmarks are calculated using the method discussed for effective spreads.

2.2 Low-frequency spread proxies

The low-frequency spread proxies, which are based on the measures used by Goyenko, Holden, and Trzcinka (2009), Hasbrouck (2009), Holden (2009), and Corwin and Schultz (2011), are discussed below.

2.2.1 Roll. We follow Goyenko, Holden, and Trzcinka (2009) and use a modified version of the Roll (1984) effective spread estimator, as expressed in Equation (4):

$$\text{Roll} = \begin{cases} 2\sqrt{-Cov\,(\Delta P_t, \Delta P_{t-1})} & \text{when } Cov\,(\Delta P_t, \Delta P_{t-1}) < 0 \\ 0 & \text{when } Cov\,(\Delta P_t, \Delta P_{t-1}) \geq 0. \end{cases} \tag{4}$$

As Equation (4) indicates, the Roll formula uses the serial covariance of the price changes as an estimate of spread. For each commodity, we compute the Roll spread in each month.

19 We require data for five days in a month in order for that month to be included in our sample.

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2.2.2 Effective Tick. Goyenko, Holden, and Trzcinka (2009) and Holden (2009) jointly develop an effective spread measure that accounts for price clustering.[20] It involves identifying mutually exclusive effective spreads, S_j, for a number of price-clustering regimes and determining the probability of the j^{th} spread, Y_j, $(j = 1, 2, \ldots, J)$. The Effective Tick measure is a probability-weighted average of each effective spread size divided by the average price in the examined time interval:

$$\text{Effective Tick} = \sum_{j=1}^{J} \gamma_j S_j / \overline{P}, \tag{5}$$

$$\gamma_j = \begin{cases} \text{Min}[\text{Max}\{U_j, 0\}, 1], & j = 1 \\ \text{Min}\left[\text{Max}\{U_j, 0\}, 1 - \sum_{k=1}^{j-1} \gamma_k\right], & j = 2, 3, \ldots, J, \end{cases} \tag{6}$$

$$U_j = \begin{cases} \left(\frac{A_1}{B_1}\right) F_1, & j = 1 \\ \left(\frac{A_j}{Bj}\right) F_j - \sum_{k=1}^{j-1} \left(\frac{O_{jk}}{B_k}\right) F_k, & j = 2, 3, \ldots, J, \end{cases} \tag{7}$$

$$F_j = \frac{N_j}{\sum_{J=1}^{j} N_j}, \quad j = 1, 2, \ldots, j, \tag{8}$$

where γ_j and U_j are the constrained and unconstrained probabilities of the j^{th} spread; A_j and B_j are the number of trade prices and special prices, respectively, corresponding to the j^{th} spread $(j = 1, 2, \ldots, k, \ldots, J)$; 0_{jk} is the number of price increments for the j^{th} spread that overlap the price increments of the k^{th} spread and do not overlap the price increments of any spreads between the j^{th} and k^{th} spreads;[21] F_j is the probability of trades on prices corresponding to the j^{th} spread; and N_j is the number of trades on prices corresponding to the j^{th} spread.

Commodity futures do not have the same minimum tick size rule. Aluminum, Brent crude oil, copper, lead, nickel, sugar, West Texas crude oil, and zinc all have a decimal tick size quotation unit. For these eight commodity

[20] Goyenko, Holden, and Trzcinka (2009) and Holden (2009) also develop two related measures: LOT Y-split and Holden (Holden 2009). We choose Effective Tick because Goyenko, Holden, and Trzcinka (2009, p. 179) state that "considering ease of computation, Effective Tick is the best measure to use."

[21] Following Goyenko, Holden, and Trzcinka (2009) and Holden (2009), the values of A_j, B_j, and O_{jk} for a decimal tick size are as follows. Please refer to www.kelley.iu.edu/cholden/examples.pdf for more information.

J	Possible Spreads	A_j	B_j	O_{jk}
1	\$0.01	100	80	
2	\$0.05	20	8	$O_{21} = 20$
3	\$0.10	10	8	$O_{31} = 0$; $O_{32} = 10$
4	\$0.50	4	3	$O_{41} = 0$; $O_{42} = 2$; $O_{43} = 2$
5	\$1.00	1	1	$O_{51} = O_{52} = O_{53} = O_{54} = 1$

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futures, we use five possible effective spread sizes ($J = 5$): 0.01, 0.05, 0.10, 0.50, and 1. Some commodity futures have quotation tick sizes that are smaller than a decimal tick: for instance, a 0.0025 tick for feeder cattle, lean hog, and live cattle; a 0.001 tick for natural gas; and a 0.0001 tick for heating oil and RBOB gasoline. Other commodity futures have quotation tick sizes that are larger than a decimal tick: for example, a 0.05 tick for coffee and gasoil; a 0.1 tick for gold; a 0.25 tick for corn, red wheat, soybeans, and wheat; a 0.5 tick for silver; and a 1.0 tick for cocoa. We specify possible effective spread sizes of non-decimal tick commodities as a multiple of the possible effective spread sizes of the decimal tick. For example, for a 0.001 minimum tick size, the possible effective spread sizes are 0.001, 0.005, 0.01, 0.05, and 0.1, and the values of A_j, B_j, and O_{jk} are adjusted accordingly.[22]

2.2.3 Gibbs. Hasbrouck (2004, 2009) advocates a Bayesian Gibbs sampling approach to the Roll model.[23] Roll (1984) suggests the following simple model of price dynamics in a market with transaction costs:

$$\Delta_{pt} = c\Delta qt + u_t, \tag{9}$$

where p_t is the log trade price, c is the first auto covariance of price changes or one-half of the posted bid-ask spread, and q_t is a trade indicator. Hasbrouck (2009) generalizes the Roll model by adding a market factor:

$$\Delta_{pt} = c\Delta qt + \beta_m r_{m,t} + u_t. \tag{10}$$

We estimate the half-spread c in the above regression using the standard Bayesian normal regression model. The prior for c is the normal distribution with a mean of 0.01 and a variance of 0.01^2 restricted to non-negative values. The priors for β_m and σ_u^2 are $N(\mu = 1, \sigma^2 = 1)$ and the inverted gamma $IG\left(\alpha = 10^{-12}, \beta = 10^{-12}\right)$, respectively. The sampler is drawn in four steps. Step one initializes the trade indicator q_1 to $+1$, and σ_u^2 is initially set to 0.01. Here, c and β_m do not require initial values because they are drawn first. Step two uses the most recently simulated q_t and σ_u^2 to calculate the posterior regression coefficients c and β_m and make a new draw. Step three uses c, β_m, and q_t to compute the implied u_t, update posterior σ_u^2 values, and make a new draw. Step four uses c, β_m, and σ_u^2 to draw $q_1, q_2, \ldots, q_T$ and goes back to step two. Each sampler is run for 1,000 sweeps, and the first 200 are thrown away as the “burn-in” sampler to minimize the impact of the initial values. The average of the draws is a point estimate in the analysis.[24]

22 For more information, see Appendix A of Holden (2009) and www.kelley.iu.edu/cholden/examples.pdf.

23 We thank Joel Hasbrouck for making his code available on his website: http://pages.stern.nyu.edu/∽jhasbrou/Research/GibbsCurrent/Programs/RollGibbsLibrary02.sas. We use his code in our article.

24 The interested reader should refer to Hasbrouck (2009, p. 1451) for a more detailed explanation.

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2.2.4 Zeros. Lesmond, Ogden, and Trzcinka (1999) suggest that the proportion of days with zero returns is a liquidity proxy. The authors propose that days of zero volume (and therefore zero return) are likely to be more prevalent in less liquid stocks. Their Zeros proxy is given in Equation (11):

$$\text{Zeros} = \frac{\#\,\text{of days with zero returns}}{T}, \tag{11}$$

where T is the total number of trading days in a month. A variation of the Zeros measure, which Goyenko, Holden, and Trzcinka (2009) refer to as Zeros2, considers the number of positive volume days that have zero return. As the authors note, there is less incentive to acquire private information in stocks with higher transaction costs. This implies that, even on days when trades do take place, it is more likely that no new information is impounded into price or zero returns. The Zeros2 measure is calculated as follows:

$$\text{Zeros2} = \frac{\#\,\text{of positive} - \text{volume days with zero returns}}{T}. \tag{12}$$

2.2.5 High-low spread estimator. Corwin and Schultz (2011) take an innovative approach to developing a new liquidity proxy based on high and low prices. The authors note that daily high (low) prices tend to be buy (sell) orders, which implies that the ratio of a stock's high (H) to low (L) prices is comprised of the stock's variance and spread. High-low price ratios estimated over a two-day period should have a variance that is twice the variance over a one-day period, but the bid-ask spread component should be the same. This fact allows Corwin and Schultz (2011) to estimate bid-ask spreads from high-low data. These authors show that their proxy does a good job of measuring actual spreads (based on intra-day data) and outperforms other liquidity proxies. The Corwin and Schultz (2011) spread estimator is given in Equation (13):

$$S = \frac{2\,(e^{\alpha} - 1)}{1 + e^{\alpha}}, \tag{13}$$

where α is

$$\alpha = \frac{\sqrt{2\beta} - \sqrt{\beta}}{3 - 2\sqrt{2}} - \sqrt{\frac{Y}{3 - 2\sqrt{2}}}. \tag{14}$$

Corwin and Schultz (2011) calculate β as in Equation (15) and Y as in Equation (16):

$$\beta = \sum_{j=0}^{1} \left[ln\left(\frac{H^0_{t+j}}{L^0_{t+j}} \right) \right]^2, \tag{15}$$

$$Y = \left[ln\left(\frac{H^0_{t,t+1}}{L^0_{t,t+1}} \right) \right]^2, \tag{16}$$

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where $H^0_{t,t+1}$ and $L^0_{t,t+1}$ are the observed high and low prices over the two days t and $t+1$, respectively. The authors note that there are a number of assumptions implicit in the High-Low measure that do not reflect reality. For example, trading is assumed to take place continuously, with prices not changing when markets are closed. We follow each of the steps outlined in Sections 2.1–2.3 of Corwin and Schultz (2011) to account for these issues.

2.2.6 FHT. Fong, Holden, and Trzcinka (2010) develop a new measure of effective spread that they call FHT. The authors find that this measure is simpler yet performs better as a spread proxy than other measures, such as LOT Mixed and Y-split. As they show, FHT can be calculated according to Equation (17), where σ is the standard deviation of the commodity's daily returns, z is the proportion of zero returns, and $N^{-1}(\,)$ is the inverse of the cumulative normal function:

$$FHT = 2\sigma N^{-1}\left(\frac{1+Z}{2}\right). \tag{17}$$

2.2.7 Other proxies. We also follow Goyenko, Holden, and Trzcinka (2009) and include the Amihud illiquidity and Amivest liquidity proxies in the correlation tests with the spread liquidity benchmarks. These measures are price impact rather than spread proxies, so we discuss them in more detail in Section 2.3.

2.3 Price-impact proxies

The low-frequency price-impact proxies are based on the measures used by Goyenko, Holden, and Trzcinka (2009). We also generate price-impact proxies from the Hasbrouck (2009) and Corwin and Schultz (2011) spread measures, using the approach of scaling by the average daily dollar volume advocated by Goyenko, Holden, and Trzcinka (2009). Other price-impact measures include the following.

2.3.1 Amihud. Amihud (2002) developed the illiquidity measure expressed in Equation (18). This proxy measures price changes per unit of dollar volume:

$$\text{Amihud} = \frac{|r_t|}{\text{volume}_t}, \tag{18}$$

where r_t is the return on day t and $Volume_t$ is the dollar volume on day t. This ratio can be calculated only on days with positive volume. The monthly proxy is the average of the daily measures.

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2.3.2 Amivest. The second price-impact liquidity proxy is the Amivest measure, which divides the volume on day t by the absolute return on day t:

$$\text{Amivest} = \frac{volume_t}{|r_t|}. \tag{19}$$

The average of these ratios is then calculated for each month. Researchers who use this proxy include Amihud, Mendelson, and Lauterbach (1997) and Berkman and Eleswarapu (1998).

2.3.3 Pástor and Stambaugh. The Pástor and Stambaugh (2003) (PS) liquidity measure, which the authors refer to as gamma (γ), is calculated as follows:[25]

$$r^e_{t+1} = \theta + \phi r_t + \gamma \, sign\left(r^e_t\right) Volume_t + \varepsilon_t, \tag{20}$$

where r^e_t is the daily commodity's excess return relative to the S&P GSCI return on day t; r_t is the daily commodity return; $sign(r^e_t)$ is one if r^e_t is positive, and zero otherwise; and $Volume_t$ is the dollar volume on day t. As Pástor and Stambaugh (2003) note, γ is expected to be positive on average, and the larger the γ in absolute terms, the lower the liquidity.

2.3.4 Other impact proxies. We follow Goyenko, Holden, and Trzcinka (2009) and calculate impact measures for each of the spread proxies by scaling the average spread measure in month i by the average daily dollar volume in month i. For instance, the Roll impact measure is

$$\text{Roll Impact}_i = \frac{\text{Roll}_i}{\text{Average Daily Dollar Volume}_i}. \tag{21}$$

This approach is used to create Effective Tick, Gibbs, Zeros, Zeros2, High-Low, and FHT impact proxies.

3. Liquidity Proxy Results

This section presents and discusses medians for each high-frequency benchmark and low-frequency proxy. We provide the correlation results and discuss their implications. Finally, we present root mean squared error results that measure the differences in scale between the liquidity benchmarks and liquidity proxies.

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[25] We follow Goyenko, Holden, and Trzcinka (2009) and use the words *gamma* and *volume* in the equation rather than symbols.

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3.1 Liquidity benchmark and proxy medians

Panel A of Table 1 shows the medians (in percentage) for the two spread benchmarks (effective spread and quoted spread) and seven spread proxies (Roll, Effective Tick, Gibbs, Zeros, Zeros2, High-Low, and FHT).[26] Since the high-frequency data in our sample begin in January 1996 and end in August 2009, the maximum number of months is 164. The last row in Table 1 shows that the average median effective and quoted spreads across all commodities are 0.16% and 0.18%, respectively. Goyenko, Holden, and Trzcinka (2009) report a median effective spread of 1.6% and a minimum firm month effective spread of 0.01% for 400 randomly selected U.S. stocks. The median of highly liquid commodities is closer to the minimum than the median for stocks, as expected.

The number of commodities that have a median Zeros and Zeros2 of 0.0000 is indicative of the high liquidity of these series because there are very few days with zero returns. The FHT measure also has a median of 0.0000 in many commodities, due to the inclusion of the proportion of zero returns in the numerator of this calculation. Panel B of Table 1 contains the medians for the price-impact benchmark and proxies. The lack of volume data for the industrial metals means we are unable to calculate price-impact measures for these commodities. A comparison of liquidity levels across commodities based on the data in Table 1 is problematic due to the different starting points for the different commodities, but we analyze this issue in depth later.

3.2 Correlations

Table 2 presents the Spearman correlation coefficients for the effective spread and each of the spread liquidity proxies. We follow Goyenko, Holden, and Trzcinka (2009) and investigate the ability of Amihud and Amivest to proxy for the spread benchmark. We expect positive correlations for all proxies for transaction costs except Amivest, which, due to its specification, should have negative correlations. Correlations that are statistically significant at the 10% level or higher are marked with a star (*). We also measure the average cross-sectional correlation across the nineteen commodities (i.e., excluding industrial metals) that have dollar volume data. All the proxies can be measured for these commodities. The average for the twenty-four commodities relates only to those proxies that do not require a dollar volume, which include Roll, Effective Tick, Gibbs, Zeros, and FHT. It is clear that the Amihud measure has the largest correlation (0.550) across the nineteen commodities with dollar volume data. The Amivest (−0.484), Effective Tick (0.399), and Zeros2 (0.146) correlations are also statistically significant. We test the null hypothesis that the Amihud correlation is equal to each of the other proxy correlations (separately by proxy) and can reject this at the 10% level for each proxy other than Amivest.

[26] Other summary statistics are available from the authors on request.

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Table 1
Benchmark and proxy medians

Panel A: Spread benchmarks and proxies

		Benchmarks			Proxies					
	N	Effective	Quoted	Roll	Eff Tick	Gibbs	Zeros	Zeros2	High-Low	FHT
Aluminum	37	0.2240	0.2050	0.6238	0.0008	0.5469	0.0000	–	–	0.0000
Brent Crude Oil	68	0.0370	0.0440	1.0853	0.0186	0.2417	0.0000	0.0000	0.6412	0.0000
Cocoa	17	0.1190	0.1550	1.6913	0.0467	0.7697	0.0000	0.0000	0.7245	0.0000
Coffee	17	0.0880	0.0910	1.4482	0.0473	0.6208	0.0000	0.0000	0.7101	0.0000
Copper	36	0.2010	0.2230	1.2672	0.0005	0.6613	0.0000	–	–	0.0000
Corn	161	0.1460	0.1230	0.4852	0.1128	0.4271	4.7619	4.5455	0.3579	0.1995
Cotton	17	0.0900	0.1140	0.2784	0.0219	0.5053	0.0000	0.0000	0.7797	0.0000
Feeder Cattle	164	0.1860	0.0820	0.2503	0.0321	0.2663	0.0000	0.0000	0.2290	0.0000
Gasoil	112	0.0880	0.1440	0.5404	0.0252	0.6680	0.0000	0.0000	0.3862	0.0000
Gold	114	0.0970	0.0670	0.2974	0.0330	0.3404	4.3478	0.0000	0.1543	0.0675
Heating Oil	164	0.1820	0.1730	0.9745	0.0141	0.3169	4.3478	0.0000	0.6405	0.1484
Lead	37	0.4180	0.5660	0.0000	0.0016	0.8074	0.0000	–	–	0.0000
Lean Hogs	164	0.1520	0.1400	0.4976	0.0481	0.5014	0.0000	0.0000	0.3751	0.0000
Live Cattle	164	0.0830	0.0980	0.3395	0.0369	0.3016	0.0000	0.0000	0.2563	0.0000
Natural Gas	154	0.1960	0.1910	1.3883	0.0301	0.8326	0.0000	0.0000	0.9190	0.0000
Nickel	37	0.4160	0.5490	0.0000	0.0000	1.0163	0.0000	–	–	0.0000
RBOB Gasoline	46	0.0810	0.0760	0.9544	0.0059	0.3293	4.3478	0.0000	0.7312	0.1775
Red Wheat	164	0.1070	0.1090	0.1231	0.0913	0.4475	2.1739	0.0000	0.3751	0.0414
Silver	99	0.1970	0.1680	0.8241	0.0974	0.5491	0.0000	0.0000	0.3049	0.0000
Soybeans	158	0.0890	0.0720	0.6754	0.0522	0.4507	4.5455	0.0000	0.3838	0.1182
Sugar	17	0.0840	0.1030	1.1602	0.0855	0.6337	0.0000	0.0000	0.8463	0.0000
West Texas Crude Oil	164	0.1100	0.0720	1.0045	0.0364	0.2603	4.3478	0.0000	0.6393	0.1618
Wheat	164	0.1720	0.1270	0.5550	0.0907	0.5345	4.5455	0.0000	0.4860	0.1691
Zinc	37	0.3860	0.5190	0.8678	0.0010	0.8451	0.0000	–	–	0.0000
Average Median		0.1645	0.1755	0.7222	0.0388	0.5364	1.3924	0.2392	0.5232	0.0451

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Table 1
Continued

Panel B: Price-impact benchmark and proxies

	Price impact	Proxies									
	b/mark	Roll	Eff Tick	Gibbs	Zeros	Zeros2	High-Low	FHT	PS	Amihud	Amivest
Aluminum	0.2010	–	–	–	–	–	–	–	–	–	–
Brent Crude Oil	0.0300	0.0218	0.0005	0.0058	0.0000	0.0000	0.0195	0.0000	−0.0010	0.0459	60.210
Cocoa	0.0820	0.6958	0.0309	0.5049	0.0000	0.0000	0.4320	0.0000	−0.1623	1.7063	2.859
Coffee	0.0520	0.2947	0.0111	0.1426	0.0000	0.0000	0.1712	0.0000	−0.0226	0.6148	8.951
Copper	0.2170	–	–	–	–	–	–	–	–	–	–
Corn	0.0660	0.0560	0.0258	0.0857	1.2697	0.6831	0.0695	0.0385	−0.0129	0.1999	8.512
Cotton	0.0740	0.0621	0.0086	0.2464	0.0000	0.0000	0.3325	0.0000	0.0253	0.9721	4.916
Feeder Cattle	0.1330	0.3448	0.0531	0.4193	0.0000	0.0000	0.3748	0.0000	−0.1379	1.0181	2.201
Gasoil	0.0680	0.1745	0.0107	0.3029	0.0000	0.0000	0.1731	0.0000	−0.2187	0.7160	3.235
Gold	0.0290	0.0272	0.0119	0.0569	0.1074	0.0000	0.0158	0.0040	−0.0065	0.5225	12.284
Heating Oil	0.0800	0.1300	0.0030	0.0647	0.1413	0.0000	0.1260	0.0070	0.0007	0.4326	9.568
Lead	0.4920	–	–	–	–	–	–	–	–	–	–
Lean Hogs	0.1360	0.2480	0.0388	0.3782	0.0000	0.0000	0.2668	0.0000	−0.0606	0.8747	2.913
Live Cattle	0.0750	0.0996	0.0154	0.1059	0.0000	0.0000	0.1006	0.0000	−0.0284	0.2568	8.842
Natural Gas	0.1430	0.1452	0.0036	0.1027	0.0000	0.0000	0.1141	0.0000	0.0047	0.3408	9.590
Nickel	0.4710	–	–	–	–	–	–	–	–	–	–
RBOB Gasoline	0.0620	0.0548	0.0004	0.0185	0.1490	0.0000	0.0404	0.0069	−0.0020	0.1235	21.002
Red Wheat	0.1120	0.1230	0.0936	0.4150	0.4734	0.0000	0.3398	0.0228	−0.0732	1.0698	2.046
Silver	0.0530	0.1695	0.0513	0.1608	0.0000	0.0000	0.0851	0.0000	−0.0177	0.4831	5.883
Soybeans	0.0570	0.0666	0.0055	0.0426	0.3196	0.0000	0.0349	0.0110	−0.0008	0.1043	22.152
Sugar	0.0590	0.1417	0.0128	0.0964	0.0000	0.0000	0.1113	0.0000	0.0012	0.2416	9.416
West Texas Crude Oil	0.0640	0.0164	0.0019	0.0123	0.0320	0.0000	0.0299	0.0014	−0.0003	0.0904	32.795
Wheat	0.0900	0.1693	0.0376	0.2050	1.2761	0.0000	0.1831	0.0573	−0.0157	0.5213	4.118
Zinc	0.3940	–	–	–	–	–	–	–	–	–	–
Average Median	0.1350	0.1601	0.0219	0.1772	0.1983	0.0360	0.1590	0.0078	−0.0383	0.5439	12.18

Panel A (B) contains the medians of the high-frequency spread (price-impact) benchmarks and low-frequency spread (price-impact) proxies. Data start in January 1996, or whenever the data become available, and finish in August 2009. N is the number of monthly observations. This is based on the quoted spread benchmark. Other benchmarks have fewer months for some commodities. Each benchmark is the median of the monthly observations, which are, in turn, calculated as the average of the intra-day benchmark calculations. Effective spreads are measured as two times the absolute value of the natural log of the trade price minus the natural log of the quote midpoint prevailing at the time of the trade. The quoted spread is the ask price minus the bid price divided by the mid-price. The low-frequency spread measures include Roll from Roll (1984), Effective Tick from Goyenko, Holden, and Trzcinka (2009), Gibbs from Hasbrouck (2009), Zeros and Zeros2 from Lesmond, Ogden, and Trzcinka (1999), high-low from Corwin and Schultz (2011), and FHT from Fong, Holden, and Trzcinka (2010). Each spread benchmark and proxy is reported as a percentage. The price-impact benchmark is the simple monthly average of the intra-day price-impact benchmarks. These are measured as two times the natural log of the spread midpoint five minutes after the trade minus the natural log of the midpoint at the time of the trade when the trade is a buy, and two times the natural log of the quote midpoint at the time of the trade minus the quote midpoint in five minutes when the trade is a sell. The first six low-frequency price-impact measures, based on the suggestion of Goyenko, Holden, and Trzcinka (2009), divide the Roll (1984), Effective Tick, Gibbs, Zeros, Zeros2, high-low, and FHT measures for month i by the average daily dollar volume within month i. We also include the Pástor and Stambaugh (PS) (2003), Amihud, and Amivest impact measures. Each of the price-impact proxies is multiplied by 10^{10}, with the exception of the Amivest measure, which is divided by 10^{10}. The price-impact benchmark, which is reported as a percentage, is not scaled.

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Table 2
Correlations with the effective spread benchmark

	Roll	Eff Tick	Gibbs	Zeros	Zeros2	High-Low	FHT	Amihud	Amivest
Aluminum	−0.193	0.257	0.472*	0.133	–	–	0.242	–	–
Brent Crude Oil	0.268*	0.544*	0.541*	0.227*	0.159	−0.097	0.263*	0.670*	−0.598*
Cocoa	−0.105	0.005	−0.211	0.037	0.037	−0.275	0.039	0.814*	−0.382
Coffee	0.000	0.154	0.240	0.407	0.407	−0.235	0.389	0.919*	−0.228
Copper	0.326*	0.212	0.436*	0.193	–	–	0.220	–	–
Corn	−0.159	0.642*	−0.245*	0.118	0.223*	−0.433*	−0.057	0.450*	−0.574*
Cotton	0.549*	0.650*	0.446*	−0.036	0.127	0.346	−0.063	0.831*	−0.691*
Feeder Cattle	0.116	0.024	0.264	−0.004	−0.106	0.100	−0.023	−0.074	−0.083
Gasoil	−0.072	0.339*	−0.383*	0.127	0.155	−0.343*	0.073	0.290*	−0.301*
Gold	−0.051	0.559*	−0.321*	0.088	0.237*	−0.528*	−0.112	0.253*	−0.322*
Heating Oil	−0.031	0.787*	0.372*	0.002	0.220*	−0.435*	−0.029	0.894*	−0.799*
Lead	0.022	0.150	0.265	0.131	–	–	0.126	–	–
Lean Hogs	0.253*	−0.101	0.245*	−0.131	0.089	0.283*	−0.122	0.365*	−0.433*
Live Cattle	−0.254*	0.044	−0.179	−0.250*	−0.111	−0.028	−0.288*	0.247*	−0.177
Natural Gas	0.061	0.621*	0.151*	−0.101	0.119	−0.118	−0.075	0.875*	−0.766*
Nickel	0.206	0.436*	0.386*	0.122	–	–	0.163	–	–
RBOB Gasoline	0.234	0.526*	0.522*	0.125	0.165	0.114	0.237	0.809*	−0.756*
Red Wheat	−0.233*	0.372*	−0.188	0.204	0.321*	−0.328*	0.056	0.441*	−0.451*
Silver	0.121	0.416*	0.019	0.044	0.213*	−0.199	−0.066	0.178*	−0.207*
Soybeans	0.118	0.532*	0.126	−0.091	0.031	−0.073	−0.091	0.396*	−0.416*
Sugar	0.148	0.201	−0.115	−0.026	−0.026	−0.066	0.000	0.775*	−0.600*
West Texas Crude Oil	−0.205*	0.803*	0.623*	−0.039	0.124	−0.326*	−0.020	0.923*	−0.886*
Wheat	−0.109	0.465*	−0.441*	0.177*	0.391*	−0.482*	0.002	0.392*	−0.531*
Zinc	0.136	0.026	0.336*	0.151	–	–	0.150	–	–
Average - 19 Commodities	0.034#	0.399*#	0.077#	0.046#	0.146*#	−0.164*#	0.006#	0.550*	−0.484*
Average - 24 Commodities	0.048	0.361*	0.140*	0.067*			0.042		

Table 2 contains the Spearman correlation coefficients between the effective spread benchmark and the spread of the Amihud and Amivest liquidity proxies. * indicates correlations that are statistically significant at the 10% level. # indicates that the null hypothesis, that the mean Amihud correlation is equal to the other proxy correlation, can be rejected at the 10% level.

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Across the nineteen commodities with dollar volume data, the Amihud proxy has a positive statistically significant correlation in all commodities except feeder cattle. This compares to a (correct:incorrect) ratio of 15:0 and 13:0, respectively, for Amivest and Effective Tick. None of the Roll, Gibbs, Zeros, Zeros2, High-Low, and FHT proxies have more than seven positive statistically significant correlations across the nineteen commodities. Some of these proxies even have statistically significant correlations with the incorrect sign in some commodities, which is difficult to explain.

These results suggest that a researcher who has dollar volume data should use the Amihud measure or, more ideally, Amihud, Amivest, and Effective Tick. However, a researcher who wishes to include all twenty-four commodities in a sample or who does not have access to dollar volume data for any commodities cannot apply the Amihud measure. We suggest that someone in this situation use the Effective Tick proxy, which has an average correlation of 0.361. Its ratio of correct to incorrect signs across commodities is also high (14:0).

Table 3 shows the correlations between the quoted spread benchmark and various spread proxies. For the nineteen commodities with dollar volume data, the Amihud measure has the largest correlation, followed by Amivest, Effective Tick, and Zeros2. We reject the null hypothesis that the Amihud average correlation is equal to that for each of the other proxies except Amivest and Effective Tick. These results are broadly consistent with those of the effective spread benchmark. The splits between statistically significant correlations (number with correct sign first) across the nineteen commodities for which all proxies can be calculated are Roll 3:3, Effective Tick 13:0, Gibbs 4:1, Zeros 5:2, Zeros2 9:0, High-Low 0:10, FHT 2:1, Amihud 17:0, and Amivest 14:0. Amihud again has the largest number of positive and statistically significant correlations, and the size of the correlations is often large. A total of ten of the correlations are in excess of 0.7.

As in Table 2, the quoted spread benchmark results show that a researcher who does not have access to dollar volume data should use the Effective Tick measures. This measure has the largest average correlations across all twenty-four commodities and performs well in the majority of industrial metal series.

The price-impact benchmark correlation results, presented in Table 4, are similar to the spread benchmark results. Based on the number of commodities with statistically significant correct signs versus incorrect signs, the Amihud measure is the best proxy, followed by Amivest, Gibbs Impact, Effective Tick Impact, and High-Low Impact. The null hypothesis, that the average Amihud correlation is equal to that of Amivest, Effective Tick Impact, Gibbs Impact, and High-Low Impact, cannot be rejected at the 10% level. However, the Amihud proxy is a more consistent performer across the individual commodities (sixteen out of a possible nineteen positive and statistically significant correlations and only one negative statistically significant correlation) compared to most of the other proxies.

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Table 3
Correlations with the quoted spread benchmark

	Roll	Eff Tick	Gibbs	Zeros	Zeros2	High-Low	FHT	Amihud	Amivest
Aluminum	−0.239	0.331*	0.363*	0.044	–	–	0.125	–	–
Brent Crude Oil	0.177	0.580*	0.542*	0.244*	0.122	−0.254*	0.285*	0.795*	−0.701*
Cocoa	−0.148	0.049	−0.255	0.149	0.149	−0.350	0.140	0.863*	−0.297
Coffee	0.005	0.098	0.184	0.491*	0.491*	−0.233	0.461*	0.926*	−0.289
Copper	0.303*	0.457*	0.554*	0.293*	–	–	0.310*	–	–
Corn	−0.178*	0.620*	−0.199	0.102	0.175*	−0.457*	−0.044	0.312*	−0.432*
Cotton	0.558*	0.757*	0.358	−0.036	0.127	0.279	−0.059	0.892*	−0.669*
Feeder Cattle	0.178	−0.007	0.186	0.010	−0.075	0.015	−0.011	−0.112	0.027
Gasoil	0.079	0.833*	−0.064	0.171*	0.209*	−0.159*	0.141	0.844*	−0.856*
Gold	0.041	0.520*	−0.148	0.171*	0.196*	−0.531*	0.021	0.442*	−0.458*
Heating Oil	−0.029	0.795*	0.357*	0.040	0.230*	−0.383*	0.012	0.909*	−0.789*
Lead	0.097	0.435*	0.546*	0.392*	–	–	0.393*	–	–
Lean Hogs	0.116	−0.162	0.038	−0.034	0.214*	0.128	−0.037	0.226*	−0.306*
Live Cattle	−0.266*	−0.071	−0.176	−0.287*	−0.114	−0.069	−0.349*	0.194	−0.154
Natural Gas	0.064	0.704*	0.118	−0.148*	0.073	−0.103	−0.123	0.884*	−0.804*
Nickel	0.180	0.946*	0.304*	0.061	–	–	0.102	–	–
RBOB Gasoline	0.110	0.561*	0.484*	0.134	0.188	−0.089	0.230	0.880*	−0.800*
Red Wheat	−0.157	0.236*	0.015	0.050	0.189	−0.302*	−0.049	0.353*	−0.197
Silver	0.219*	0.438*	0.022	0.148	0.232*	−0.220*	0.027	0.306*	−0.299*
Soybeans	0.009	0.540*	−0.019	−0.093	0.006	−0.228*	−0.125	0.389*	−0.462*
Sugar	0.163	0.260	−0.169	−0.059	−0.059	−0.125	−0.033	0.782*	−0.598*
West Texas Crude Oil	−0.227*	0.709*	0.540*	0.020	0.160*	−0.328*	−0.007	0.789*	−0.750*
Wheat	−0.159	0.470*	−0.517*	0.189*	0.389*	−0.521*	−0.024	0.353*	−0.529*
Zinc	0.122	−0.045	0.623*	0.304*	–	–	0.303*	–	–
Average - 19 Commodities	0.029#	0.417*	0.068#	0.066#	0.153*#	−0.207*#	0.024#	0.580*	−0.493*
Average - 24 Commodities	0.042	0.419*	0.154*	0.098*			0.070*		

Table 3 contains the Spearman correlation coefficients between the quoted spread benchmark and the spread and Amihud and Amivest liquidity proxies. * indicates correlations that are statistically significant at the 10% level. # indicates that the null hypothesis, that the mean Amihud correlation is equal to the other proxy correlation, can be rejected at the 10% level.

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Table 4
Correlations with the price-impact benchmark

	Roll Impact	Eff Tick Impact	Gibbs Impact	Zeros Impact	Zeros2 Impact	High-Low Impact	FHT Impact	PS	Amihud	Amivest
Aluminum	–	–	–	–	–	–	–	–	–	–
Brent Crude Oil	0.260*	0.512*	0.614*	0.155	0.105	0.631*	0.170	−0.218*	0.665*	−0.574*
Cocoa	0.048	0.451*	0.162	0.337	0.337	0.086	0.333	0.093	0.115	0.093
Coffee	0.065	0.103	0.306	0.010	0.010	0.020	−0.040	0.321	0.466*	−0.522*
Copper	–	–	–	–	–	–	–	–	–	–
Corn	0.095	0.689*	0.522*	0.268*	0.293*	0.435*	0.249*	−0.255*	0.461*	−0.552*
Cotton	0.642*	0.645*	0.696*	0.145	0.131	0.632*	0.158	−0.135	0.488*	−0.505*
Feeder Cattle	0.017	−0.170	0.073	0.063	−0.028	−0.070	0.017	−0.185	−0.028	−0.074
Gasoil	0.288*	0.887*	0.783*	0.224*	0.242*	0.760*	0.243*	−0.527*	0.883*	−0.876*
Gold	0.150	0.101	0.149	0.032	0.159	0.219*	0.085	−0.125	0.159	−0.150
Heating Oil	0.210*	0.643*	0.632*	0.191*	0.165*	0.558*	0.188*	−0.054	0.598*	−0.549*
Lead	–	–	–	–	–	–	–	–	–	–
Lean Hogs	0.237*	0.289*	0.398*	−0.090	0.125	0.420*	−0.096	−0.098	0.312*	−0.399*
Live Cattle	−0.160	0.207	0.182	−0.185	−0.049	0.291*	−0.254*	0.087	0.230*	−0.186
Natural Gas	0.333*	0.726*	0.748*	−0.070	0.114	0.714*	−0.053	0.106	0.806*	−0.699*
Nickel	–	–	–	–	–	–	–	–	–	–
RBOB Gasoline	0.420*	0.592*	0.619*	0.144	0.275*	0.486*	0.168	−0.187	0.646*	−0.596*
Red Wheat	−0.100	0.322*	0.507*	0.247*	0.283*	0.179	0.260*	−0.229*	0.439*	−0.388*
Silver	−0.055	0.124	0.184	0.017	−0.066	−0.078	0.057	0.045	0.308*	−0.211*
Soybeans	0.189*	0.506*	0.500*	0.023	0.082	0.278*	0.028	−0.210*	0.301*	−0.399*
Sugar	0.251	0.527*	0.694*	0.171	0.171	0.532*	0.171	−0.292	0.914*	−0.733*
West Texas Crude Oil	0.194*	0.868*	0.864*	0.183*	0.147*	0.863*	0.196*	0.130*	0.886*	−0.849*
Wheat	0.177	0.684*	0.521*	0.252*	0.341*	0.418*	0.185*	−0.087	0.385*	−0.520*
Zinc	–	–	–	–	–	–	–	–	–	–
Average - 19 Commodities	0.172*#	0.458*	0.482*	0.111*#	0.149*#	0.388*	0.109*#	−0.096*#	0.475*	−0.457*

Table 4 contains the Spearman correlation coefficients between the price-impact benchmark and the price-impact liquidity proxies. * indicates correlations that are statistically significant at the 10% level. # indicates that the null hypothesis, that the mean Amihud correlation is equal to the other proxy correlation, can be rejected at the 10% level.

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We also investigate whether our price-impact correlation results are robust across trade sizes. Institutional investors have an increasingly important role in commodity markets, so we check whether our results are sensitive to small, medium, or large trades. For each commodity each year, we classify trade volume from high-frequency data into three groups by size of trade, calculate the average monthly price impact for each trade size group, and then compute the Spearman correlations between these three price-impact benchmarks and low-frequency price-impact proxies. The average correlations across all nineteen commodities for different trade sizes are presented in Appendix 1. The results indicate that our correlations are stable across different trade sizes. We test the differences in correlation between small and large trade size groups, but none of these are statistically significant at the 10% level. The Amihud measure has the largest correlation in each of the three trade sizes.[27]

In summary, the Amihud measure is the best and most consistent liquidity proxy when compared to the three liquidity benchmarks. Researchers with access to dollar volume data who want to use only one proxy should use this. If they want to supplement their analysis with other proxies, they should add the Amivest and Effective Tick measures. Researchers who lack dollar volume data should use the Effective Tick measure. The consistency of the Amihud proxy across different commodities is also robust through time. For instance, in Table 3, the correlation with quoted spread is large for coffee (0.926), which only has data back to 2008, and heating oil (0.909), which has data back to 1996. Appendix 2 reports the yearly correlations for each of the liquidity proxies versus quoted spread. These show that the Amihud measure dominates other proxies in 12 of the 14 years.[28]

3.3 Root mean squared errors

Goyenko, Holden, and Trzcinka (2009) note that the root mean squared error (RMSE) is an appropriate measure to use in determining whether the scale of the liquidity proxy is consistent with the scale of the liquidity benchmark. Having the actual transaction cost scale accurately reflected by a proxy may not be critical for applications such as asset pricing research, but it is important for market efficiency studies and practitioner applications.[29] As with Goyenko, Holden, and Trzcinka (2009), we do not calculate the RMSE for Zeros, Zeros2, Amihud, or Amivest due to the measurement units that are clearly different from the benchmarks. The Table 5 results, which pertain to Roll, Effective Tick, Gibbs, High-Low, and FHT median RMSEs measures, show that none of these have a size that is consistent with the transaction cost benchmarks. The null hypothesis that the RMSE is zero can be rejected in each instance. We also

27 We thank Hank Bessembinder for suggesting that we investigate the relation between trade size and price impact.

28 We thank an anonymous referee for suggesting this analysis.

29 We thank an anonymous referee for suggesting this analysis.

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Table 5
Root mean squared errors

		Roll	Eff Tick	Gibbs	High-Low	FHT
Effective Spread	Median	0.927	0.202	0.541	0.408	0.208
	Signed Rank Test *p*-Value	0.000	0.000	0.000	0.000	0.000
Quoted Spread	Median	0.960	0.121	0.503	0.433	0.164
	Signed Rank Test *p*-Value	0.000	0.000	0.000	0.000	0.000
Price Impact	Median	0.060	0.059	0.067	0.059	0.059
	Signed Rank Test *p*-Value	0.000	0.000	0.000	0.000	0.000

This table shows the median Root Mean Squared Errors (RMSEs) by liquidity proxy and benchmark (reported as a percentage). The *p*-value relates to the statistical test that the RMSE between each benchmark and liquidity proxy is zero.

interpret the magnitude of the RMSEs to be economically significant.[30] For instance, the lowest effective spread RMSE, for the Effective Tick liquidity proxy, is 0.202, which is larger than the median effective spread itself (0.165 from Table 1). Other proxies have larger RMSEs that are more economically significant. Documenting actual trading costs for different trade sizes and execution approaches is the focus of Section 4.

4. Transaction Cost Results

This section gives insight into the costs of different execution approaches. It contains trade size summary statistics, and results for the different aspects of actual transaction costs[31] including spread, depth, resiliency, and immediacy. We document actual transaction costs under different scenarios, such as when investors are prepared to wait for different lengths of time to complete their trades and when they require immediate execution. We also report the reduction in transaction costs that occurs when trades are split into smaller components.

4.1 Trade size summary statistics

Table 6 presents the dollar value trade size summary statistics for the period April 2008 to August 2009. The starting point is determined by the date that all commodities have high-frequency data and permits comparisons across commodities.[32] No trade size data are available for industrial metal commodities, so these are not included in the analysis. For the other commodities, trade size dollar values are calculated by multiplying the number of contracts traded by the contract quantity and the price. West Texas crude oil, Brent crude oil,

30 We determine economic significance by comparing the RMSE to the magnitude of the spread. Others may use the magnitude of the RMSE itself.

31 We thank the former editor, Matthew Spiegel, and an anonymous referee for suggesting we investigate transaction cost issues.

32 Our analysis occurs in the period of the global financial crisis, so the results may not be readily applied to other periods.

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Table 6
Dollar value trade size summary statistics

	N	Min	Mean	Median	Max	StdDev
Brent Crude Oil	4,785	36	407	134	192,126	1,385
Cocoa	417	19	104	51	30,267	292
Coffee	748	38	168	85	106,794	685
Corn	2,243	15	208	64	69,533	470
Cotton	734	18	104	38	34,975	256
Feeder Cattle	69	43	119	56	6,486	148
Gasoil	1,948	36	376	125	157,376	1,472
Gold	3,317	68	339	174	59,642	569
Heating Oil	1,412	48	215	137	30,674	344
Lean Hogs	458	17	95	51	8,971	143
Live Cattle	434	32	138	71	8,913	200
Natural Gas	1,357	29	292	117	50,459	592
RBOB Gasoline	793	35	296	136	34,436	520
Red Wheat	497	24	101	56	7,386	133
Silver	1,141	44	198	89	19,382	273
Soybeans	3,876	39	272	128	93,869	521
Sugar	1,222	11	141	53	28,479	372
West Texas Crude Oil	9,377	35	320	134	58,432	608
Wheat	1,827	23	152	74	29,156	273

This table contains summary statistics for dollar value trade sizes. N is the number of trades, in thousands, and the other columns are thousands of dollars. The sample period commences in April 2008 and ends in August 2009. The dollar value trade size is computed from the quantity volume traded multiplied by the futures prices and a contract size dollar multiplier.

soybeans, and gold are the four most liquid commodities based on the number of trades. West Texas crude oil, Brent crude oil, and gold are also, together with Gasoil, the most liquid, based on mean trade sizes. Lean hogs, red wheat, cotton, and cocoa have the lowest mean trade sizes. In unreported results, we compare liquidity across commodities based on spread benchmarks. These results are consistent in terms of the most liquid commodities. However, they show that industrial metals are less liquid than those from any of the other commodity families.

4.2 Spread costs by trade size

The first measure of transaction costs we consider is spread, which is also referred to as tightness, breadth, and width (e.g., Kyle 1985; Harris 2003). Spread is the cost of transacting at the best bid or ask quote. We measure spread as the difference between transaction price and the quote midpoint prevailing at the time of the transaction, as per Equation (2). However, we report one-way transaction costs so, unlike Equation (2), we do not multiply this difference by two. We calculate mean half (effective) spreads for ten trade size buckets ranging from 0 to \$100,000 to \$900,000 and above. These calculations are carried out by commodity. Table 7 and Figure 1 contain an overall commodity result, which is the simple average for each trade size bucket across all commodities and averages for each commodity family. The half spreads relate to completed trades. Average commodity half spreads range from 3.5 basis points for trades in the 0 and \$100,000 range to 4.4 basis points for trades of \$900,000 and

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Table 7
One-way transaction costs based on effective half spreads

Trade size	(0, 100k]	(100k, 200k]	(200k, 300k]	(300k, 400k]	(400k, 500k]	(500k, 600k]	(600k, 700k]	(700k, 800k]	(800k, 900k]	900k+
Panel A: All and by family										
All	3.5	3.4	3.6	3.7	3.8	3.9	4.0	4.0	4.1	4.4
Energy	2.9	2.4	2.6	2.7	2.7	2.7	2.7	2.7	2.8	2.9
Precious Metal	2.1	2.4	2.6	2.7	2.7	3.0	3.1	3.1	3.0	3.9
Livestock	4.7	4.7	4.8	4.9	4.9	5.2	5.3	5.1	5.4	5.6
Agricultural	3.8	3.9	4.2	4.4	4.5	4.6	4.8	4.8	4.9	5.2
Panel B: By commodity										
Brent Crude Oil	2.2	1.9	1.9	2.0	2.0	1.9	1.9	1.9	1.9	1.8
Cocoa	5.0	5.2	5.3	5.8	5.7	5.6	5.7	5.9	5.9	5.9
Coffee	3.7	4.0	4.2	4.8	4.7	4.7	5.6	5.5	5.6	5.3
Corn	3.5	3.7	3.8	4.0	4.1	4.2	4.3	4.4	4.5	5.1
Cotton	4.4	4.2	4.5	4.3	4.9	4.8	4.6	4.5	4.5	4.7
Feeder Cattle	6.8	6.5	6.4	6.5	6.1	6.5	6.7	6.1	6.6	6.8
Gasoil	2.9	2.5	2.6	2.6	2.6	2.6	2.6	2.7	2.7	2.6
Gold	1.1	1.3	1.5	1.5	1.4	1.6	1.7	1.7	1.7	2.1
Heating Oil	3.5	2.8	3.0	2.7	2.7	2.8	2.6	2.8	2.7	2.8
Lean Hogs	4.5	4.6	5.0	5.3	5.5	5.6	5.6	5.7	6.2	6.2
Live Cattle	2.9	3.0	3.2	3.1	3.3	3.6	3.5	3.6	3.5	4.0
Natural Gas	2.8	2.5	2.8	3.2	3.3	3.2	3.4	3.5	3.6	4.0
RBOB Gasoil	3.8	2.9	2.9	3.1	3.1	3.2	3.1	3.0	3.1	3.5
Red Wheat	4.0	4.2	4.4	4.6	4.6	5.0	4.9	5.0	4.9	5.4
Silver	3.0	3.5	3.7	3.9	3.9	4.3	4.6	4.4	4.3	5.7
Soybeans	2.1	2.3	2.5	2.6	2.8	3.0	3.0	3.2	3.4	3.8
Sugar	3.9	4.0	4.3	4.4	4.5	4.7	4.8	4.8	4.8	5.1
West Texas Crude Oil	2.5	2.0	2.3	2.5	2.6	2.5	2.6	2.7	2.8	2.9
Wheat	3.6	4.1	4.5	4.8	5.0	5.2	5.5	5.5	5.6	6.3

Table 7 contains mean effective half spreads for different dollar value trade size buckets. The sample period commences in April 2008 and ends in August 2009. Results are reported in basis points.

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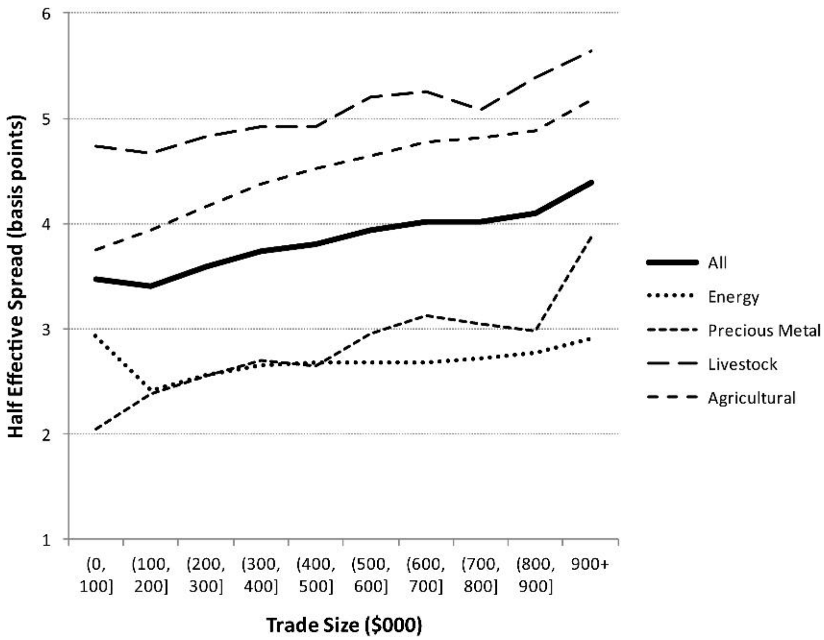

Figure 1
One-way transaction costs based on effective half spreads
This figure contains mean effective half spreads for different dollar value trade size buckets. The sample period commences in April 2008 and ends in August 2009. Results are reported in basis points.

above. Energy and precious metal commodities have the lowest transaction costs. Livestock commodities have the largest transaction costs, followed by agricultural commodities.

Larger transaction costs for larger trade sizes appear to be a reasonable expectation; however, empirical studies suggest that this is not always the case. Corporate bond market studies, such as Edwards, Harris, and Piwowar (2007) and Bao, Pan, and Wang (2011), find that transaction costs decline, on average, as trade size increases. Edwards, Harris, and Piwowar (2007) note that this may be due to institutional investors being more skilled at negotiating better prices. Moreover, Hausman, Lo, and MacKinlay (1992) explain that a negative relation between trade size and price response implies an economy of scale in trading, or a “deep” market in which large trade volumes can occur without much of a price response. The Table 7 results show that this is consistent with our Brent crude oil and heating oil results. However, all other commodities display a positive relation between trade size and transaction cost. As a robustness check, we repeat the analysis using one-way price impact rather than effective spread. These results are very similar, as shown in Appendix 3.

It is well known that transaction costs are positively related to volatility (e.g., Chordia, Sarkar, and Subrahmanyam 2005). We document the relation

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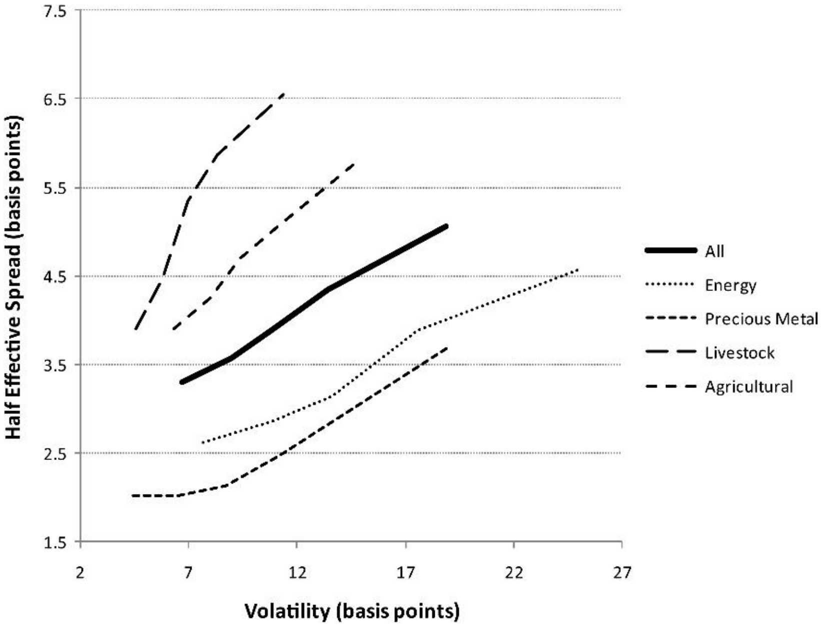

Figure 2
Transaction costs and volatility
Figure 2 shows transaction costs for different volatility buckets. Moving average volatilities, based on a five-minute window of 120 absolute changes in the midpoint, are calculated for each commodity. Average volatility is then calculated for quintiles. The average half effective spread for each quintile is calculated for each commodity. Family averages and an overall commodity average are then computed. The period is April 2008 until August 2009.

between volatility and transaction costs in Figure 2 so as to give investors insight into transaction costs they might experience if they expect lower or higher than normal volatility. First, we take a snapshot of the mid-quote point and effective half spread at five-minute intervals. Then, we calculate moving average volatilities based on a window of 120 absolute changes in the mid-point. Moving average effective half spreads are also computed for the same volatility windows. Volatilities are ranked into quintiles before the simple average spreads are calculated for each quintile. The slope of each of the lines represents the sensitivity of transaction costs to volatility. Figure 2 shows that average transaction costs increase from 3.3 basis points in the low volatility bucket to 5.1 basis points in the high volatility bucket. Energy commodities are more volatile than commodities in the other families, but the transaction costs of energy commodities are less influenced by volatility increases than those of other families. Both livestock and agricultural commodity transaction costs are particularly sensitive to changes in volatility. Appendix 4 provides detailed information on the average effective half spread and volatility level for each volatility quintile. It shows that the steep pattern for the livestock family in Figure 2 is driven by the relatively high sensitivity of feeder cattle's liquidity

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to volatility, while the pattern for energy is influenced by the relatively low sensitivity of natural gas.

4.3 Depth

Depth is the amount that can be transacted at the best bid or ask quote. The spread is only an accurate measure of transaction costs to the extent there is depth at the best bid or ask quote. If there is insufficient depth for an urgent trade to be completed, then the remaining portion of the trade would have to be executed at the second best bid or ask price. Such an occurrence would result in a higher transaction cost than if there had been sufficient depth for the order to be completed at the first level of the order book.

We measure depth using order book data, which means that our measures will be conservative to the extent that there is depth in the open-outcry segment of the market.[33] Order book data are not available for all commodities, so our analysis is based on six energy commodities (Brent crude oil, gasoil, heating oil, natural gas, RBOB gasoline, and West Texas crude oil), the two precious metals (gold and silver), and four agricultural commodities (cocoa, coffee, cotton, and sugar). We follow Kempf, Mayston, and Yadav (2009) and calculate all order book statistics based on observations of the book at five-minute intervals. We measure depth by commodity and then calculate simple averages for commodity families and all commodities. As shown in Table 8, the mean one-sided depth across all commodities is $290,000 and the average median depth across all commodities is $198,000. Precious metals and energy commodities have the highest depth, on average, and agricultural have the lowest. Of the individual commodities, gasoil has the highest depth and cocoa has the lowest.

4.4 Immediacy by trade size

Another dimension of transaction costs is the ease at which an individual can execute an order immediately and the costs they incur in doing so. If there is insufficient depth to allow complete execution of an order at the best bid or ask price, then the individual must "walk the book." This involves completing the first part of the buy (sell) order at the best ask (bid) price, the next component at the second best ask (bid) price, and so on. The amount transacted at each level depends on the value of orders sitting in the book at each level. We calculate the immediacy cost for different trade size buckets as the relative difference between the best bid and ask quote midpoint and the weighted average execution price for an investor who has "walked up or down" the book in order to execute immediately. We repeat this by hour. As shown in Table 9 and Figure 3, the cost is, on average, 6.3 basis points for trades of $100,000

[33] Investors are able to submit hidden orders where a portion of the total number of contracts in which they wish to transact are not displayed to other market participants; see http://www.cmegroup.com/globex/files/GlobexRefGd.pdf. These orders are not visible in the database so are not included in our depth calculations.

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Table 8
Depth

	Min	Mean	Median	Max	StdDev
Panel A: All and by family					
All	55	290	198	6,529	333
Energy	62	333	218	6,480	375
Precious Metal	81	394	299	9,423	391
Agricultural	31	175	117	5,156	240
Panel B: By commodity					
Brent Crude Oil	69	319	214	7,256	383
Cocoa	27	110	73	1,576	139
Coffee	45	193	136	2,710	203
Cotton	29	104	72	2,010	130
Gasoil	57	812	515	8,963	825
Gold	93	483	377	14,261	507
Heating Oil	75	182	155	3,931	163
Natural Gas	30	137	86	7,555	192
RBOB Gasoline	74	199	121	5,199	289
Silver	68	306	220	4,586	275
Sugar	21	295	187	14,330	489
West Texas Crude Oil	68	348	220	5,974	400

This table contains summary statistics for the average dollar value of depth at the bid or ask at the first level of the book. The order book is sampled every five minutes in August 2009. Each number is in thousands of dollars.

and 25.8 basis points for trades of $1,000,000. Table 9 and Figure 3 show that precious metals and energy commodities have lower transaction costs for individuals requiring immediate execution, while agricultural commodities have higher costs. West Texas crude oil has the lowest costs, ranging from 1.9 basis points for trades of $100,000 to just 4.3 basis points for trades of $1,000,000. Cocoa is the most expensive at 15.2 basis points for small trades of $100,000, while coffee is the most expensive at 99.8 basis points for large trades of $1,000,000.

One can view immediacy as the frequency at which an individual can immediately execute their trades. There are two aspects to this. First, how often can a trader fully execute their trade at the best bid or ask price? Second, how often can a trader fully execute their trade if they are prepared to walk the book and exhaust all liquidity in the book at that point? We address these two questions in Table 10. Panel A contains the answer to the first question, and Panel B the answer to the second question. The Panel A results show that, on average across all commodities, 55% of $100,000 trades can be executed at the best bid or ask price and 5% of $1,000,000 trades can be executed at the best bid or ask price. Put another way, individuals trading commodities will incur a cost greater than the half quoted spreads documented in Table 9, 45% of the time for small trades and 95% of the time for large trades. Traders of energy and precious metals commodities are more likely to be able to fully execute their trades at the best bid or ask price, while traders of agricultural commodities are less likely to be able to achieve this. Gasoil has the largest proportions of first-level complete execution, whereas cotton has the lowest proportions. However,

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Table 9
One-way transaction costs for immediate execution

	Quoted half spread	100k	200k	300k	400k	500k	600k	700k	800k	900k	1,000k
Panel A: All and by family											
All	5.1	6.3	8.9	11.9	14.7	16.9	19.1	21.5	22.9	24.3	25.8
Energy	5.5	5.2	6.8	8.5	10.6	12.8	14.6	16.5	16.9	18.4	19.4
Precious Metal	2.8	2.8	3.3	4.4	5.6	6.9	8.0	8.8	9.7	10.4	11.3
Agricultural	5.4	9.7	14.8	20.8	25.5	28.1	31.5	35.3	38.6	40.3	42.5
Panel B: By commodity											
Brent Crude Oil	3.3	3.3	4.0	5.2	5.8	6.5	7.7	8.5	9.3	10.3	11.1
Cocoa	7.8	15.2	26.6	38.3	39.7	34.0	32.6	34.6	37.4	34.5	34.7
Coffee	6.8	9.6	14.8	23.1	37.2	50.5	63.0	74.6	83.6	91.7	99.8
Cotton	7.3	9.5	12.4	15.5	17.9	20.1	21.9	23.1	24.0	24.6	24.9
Gasoil	6.5	6.5	7.7	8.4	9.3	10.3	11.1	12.0	12.9	13.7	14.5
Gold	1.8	1.8	2.1	3.0	4.9	7.0	8.6	9.9	11.4	12.7	14.2
Heating Oil	5.3	5.3	6.3	8.5	13.1	20.0	24.1	30.5	27.5	30.7	33.3
Natural Gas	6.7	8.3	13.1	15.8	18.2	18.8	20.4	21.0	21.8	22.2	22.3
RBOB Gasoline	6.3	6.3	7.7	10.4	13.9	17.6	20.2	23.2	25.7	29.0	31.2
Silver	3.9	3.9	4.5	5.7	6.3	6.9	7.3	7.7	8.0	8.2	8.4
Sugar	3.6	4.4	5.4	6.2	7.0	7.8	8.5	9.0	9.6	10.2	10.8
West Texas Crude Oil	1.9	1.9	2.2	2.8	3.1	3.5	3.8	3.9	4.1	4.2	4.3

Table 9 contains the average quoted half spread and average one-way transaction costs for individuals wanting immediate execution. These are calculated as the relative difference between the mid-price when a “trade” is placed and the dollar volume weighted average of the execution prices. If there is sufficient depth to execute half the trade at the first level of the book and the remainder at the second level of the book, the weighted average execution price will be the average of these two transaction prices. We assume the book is walked up or down until complete execution is achieved. We also record if the order cannot be fully executed and report these statistics separately. The order book is sampled every five minutes in August 2009.

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Table 10
Trade execution

Trade size	100k	200k	300k	400k	500k	600k	700k	800k	900k	1,000k
Panel A: Proportion of trades executed at the first level in the book										
All	55.2	36.4	23.4	17.7	13.4	10.5	8.7	7.1	6.1	5.2
Energy	57.0	39.0	25.1	19.2	14.9	12.2	10.6	8.9	7.8	6.9
Precious Metal	73.7	56.1	38.8	30.6	23.2	17.6	14.0	11.2	9.0	7.1
Agricultural	43.3	22.8	13.2	8.9	6.2	4.4	3.2	2.5	2.2	1.8
Brent Crude Oil	65.9	46.4	26.3	19.9	15.0	11.1	9.3	7.2	5.8	5.1
Cocoa	30.1	11.5	5.1	3.1	2.0	1.4	1.1	0.8	0.8	0.7
Coffee	52.5	28.2	15.4	10.3	6.9	4.5	3.2	2.4	2.0	1.6
Cotton	26.3	10.6	5.5	3.3	2.1	1.6	1.1	0.9	0.9	0.7
Gasoil	84.4	70.8	57.0	49.7	42.3	38.3	34.4	30.7	28.6	25.7
Gold	76.6	59.8	47.0	37.4	29.7	23.7	19.2	16.0	13.1	10.4
Heating Oil	46.3	27.0	13.2	7.7	4.3	3.4	2.7	2.0	1.5	1.2
Natural Gas	35.8	17.0	9.5	6.0	4.3	3.1	2.4	1.9	1.5	1.2
RBOB Gasoline	39.6	22.2	14.7	8.3	5.3	4.2	3.6	2.6	2.0	1.8
Silver	70.9	52.4	30.7	23.7	16.7	11.5	8.9	6.5	4.8	3.7
Sugar	64.4	40.8	26.9	18.9	13.6	10.0	7.4	5.7	4.9	4.1
West Texas Crude Oil	70.2	50.6	29.8	23.6	18.3	13.3	11.1	9.1	7.3	6.2
Panel B: Proportion of trades fully executed after walking the book										
All	100.0	99.7	98.7	96.9	93.6	89.8	85.7	81.0	76.1	71.7
Energy	100.0	99.5	97.4	94.5	89.9	85.1	80.6	75.1	70.0	66.1
Precious Metal	100.0	100.0	100.0	99.8	98.3	95.2	91.8	87.2	82.5	77.4
Agricultural	100.0	100.0	100.0	99.0	96.8	94.1	90.3	86.6	82.0	77.3
Brent Crude Oil	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	99.9	99.8
Cocoa	100.0	100.0	100.0	96.7	90.2	84.1	75.6	68.9	60.4	52.4
Coffee	100.0	100.0	100.0	100.0	100.0	100.0	99.8	99.3	98.3	96.7
Cotton	100.0	100.0	100.0	99.3	96.9	92.4	85.9	78.2	69.4	60.2
Gasoil	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Gold	100.0	100.0	100.0	100.0	98.3	95.0	90.5	85.2	79.3	73.0
Heating Oil	100.0	100.0	100.0	99.2	93.9	86.3	78.0	64.1	51.7	42.1
Natural Gas	100.0	96.9	84.4	73.9	63.6	54.5	46.9	40.4	35.2	31.1
RBOB Gasoline	100.0	100.0	100.0	94.5	84.1	77.0	69.4	61.0	53.4	47.6
Silver	100.0	100.0	100.0	99.7	98.2	95.5	93.1	89.3	85.8	81.7
Sugar	100.0	100.0	100.0	100.0	100.0	100.0	99.9	99.9	99.9	99.9
West Texas Crude Oil	100.0	100.0	100.0	99.3	97.5	92.8	89.5	85.1	79.8	76.3

Panel A reports the proportion of trades of various sizes executed at the first level of the book (in percent). Panel B contains the proportion of trades fully executed after walking the book. The order book is sampled every five minutes in August 2009.

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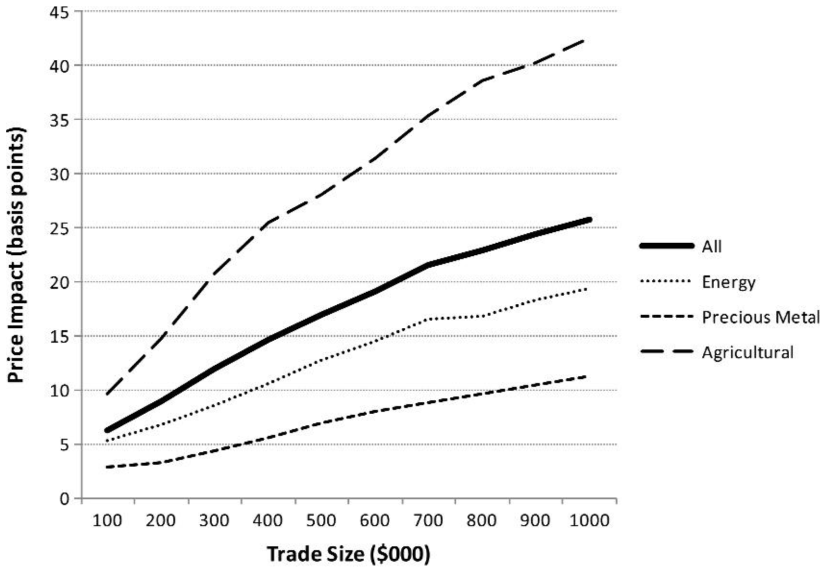

Figure 3
One-way transaction costs for immediate execution
This figure contains the average one-way transaction costs for individuals wanting immediate execution. These are calculated as the difference between the mid-price when a "trade" is placed and the dollar volume weighted average of the execution prices. The order book is sampled every five minutes in August 2009.

there is variation within the commodity families for the different trade buckets. For instance, completely executing large trades in sugar is relatively more likely than in heating oil and natural gas.

The results in Panel B of Table 9 indicate that a trader who requires immediate execution and is willing to walk the book can execute \$100,000 trades 100% of the time; \$1,000,000 trades can be executed 72% of the time, on average. In contrast to the Panel A results, which indicate less consistent depth at the first level of the book in agricultural commodities on average, Panel B shows that there is more likelihood of being able to fully execute \$1,000,000 trades in agricultural commodities than energy commodities. This implies more depth at the lower levels of the book.

4.5 Resiliency

We follow Kempf, Mayston, and Yadav (2009) and measure resiliency as the length of time it takes for spread and depth to recover following large trades.[34] This involves modeling the relationship between past and present liquidity as a "mean reversion model where liquidity reverts back to its long-run value θ with the speed of adjustment of κ" (p. 12):

[34] By large trades we mean trades that consume liquidity.

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Table 11
Resiliency

	Absolute spread		Bid depth		Ask depth	
	Kappa	t-stat	Kappa	t-stat	Kappa	t-stat
Panel A: All and by family						
All	−0.37	−7.08	−0.78	−22.87	−0.73	−17.27
Energy	−0.34	−4.39	−0.74	−22.47	−0.68	−17.81
Precious Metal	−0.36	−8.63	−0.78	−20.96	−0.73	−21.10
Agricultural	−0.41	−10.34	−0.84	−24.42	−0.81	−14.53
Panel B: By commodity						
Brent Crude Oil	−0.13	−3.63	−0.83	−22.76	−0.72	−18.09
Cocoa	−0.36	−4.07	−0.91	−18.90	−0.90	−22.97
Coffee	−0.31	−5.56	−0.70	−9.62	−0.81	−10.42
Cotton	−0.34	−14.42	−0.79	−18.95	−0.69	−8.37
Gasoil	−0.11	−3.99	−0.59	−25.46	−0.59	−24.42
Gold	−0.23	−7.59	−0.90	−24.12	−0.76	−21.97
Heating Oil	−0.39	−1.60	−0.75	−15.07	−0.71	−9.10
Natural Gas	−0.48	−4.07	−0.77	−19.64	−0.85	−17.87
RBOB Gasoline	−0.26	−8.47	−0.66	−12.95	−0.36	−5.35
Silver	−0.49	−9.68	−0.65	−17.79	−0.70	−20.22
Sugar	−0.64	−17.30	−0.97	−50.21	−0.82	−16.37
West Texas Crude Oil	−0.65	−4.56	−0.83	−38.92	−0.82	−32.03

This table contains results from the Kempf, Mayston, and Yadav (2009) market resiliency calculations. Kappa is proportion of liquidity that has been restored. These results are for a period five minutes after liquidity had been eroded by a trade. The order book is sampled in August 2009.

$$\Delta L_t = \kappa(\theta - L_{t-1}) + \varepsilon_t, \tag{22}$$

where L_t and L_{t-1} are current and past liquidity, respectively, and ε_t is a normally distributed random variable. As Kempf, Mayston, and Yadav (2009) note, the higher the κ the stronger the resiliency. Table 11 shows the κ and associated t-statistic for each commodity. We report results for absolute spreads and bid depth and ask depth (both at the first level of the book).[35] The t-statistics are adjusted for cross-sectional correlation using the method suggested by Chordia, Roll, and Subrahmanyam (2000). Simple averages of each variable are calculated for each family and commodities overall.

The Table 11 results, which relate to the five-minute interval, show that liquidity is restored relatively quickly in all commodities. Over 70% of depth and 37% of spread are restored five minutes after a trade. Liquidity returns to pre-trade levels between 30 and 60 minutes after a trade on average.

4.6 Trade splitting

Traders may attempt to minimize transaction costs by splitting their trades into smaller components. In Table 12, we present transaction costs for a trader who has $1,000,000 worth of a commodity to trade. We test various periods within which the trader requires their order to be fully executed. Since the Table 11 results indicate that approximately 70% of depth is restored within five minutes, we use this interval to execute different components of the trade. As this

[35] We also run results for relative spreads and the first three levels of the book and find these are qualitatively identical to those for absolute spreads and first-level depth, respectively.

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Table 12
One-way transaction costs for patient execution and trade splitting

	100% of Depth restored					50% of Depth restored				
	5 min	15 min	30 min	45 min	60 min	5 min	15 min	30 min	45 min	60 min
Panel A: All and by family										
All	25.1	17.5	10.0	7.5	6.5	25.2	21.5	15.3	11.3	8.6
Energy	19.9	14.4	7.6	6.8	6.5	20.0	18.1	12.2	8.4	6.7
Precious Metal	9.2	3.7	3.7	3.6	3.6	9.3	5.4	3.8	3.4	3.8
Agricultural	40.9	29.1	16.7	10.5	8.0	40.9	34.6	25.6	19.7	13.8
Panel B: By commodity										
Brent Crude Oil	17.5	11.6	6.7	5.5	5.6	17.5	13.7	9.6	5.9	5.7
Cocoa	31.8	26.7	20.4	16.4	11.0	31.8	28.7	24.7	21.6	16.8
Coffee	99.0	64.5	27.4	10.4	8.1	99.3	80.9	52.9	37.0	21.1
Cotton	24.1	19.7	14.8	11.4	9.3	24.1	22.3	19.5	16.3	13.6
Gasoil	21.8	14.7	13.7	12.4	12.2	22.0	16.8	13.4	12.8	12.7
Gold	9.8	1.9	1.8	1.8	1.8	9.9	3.7	2.1	2.1	2.2
Heating Oil	26.4	20.9	8.5	5.4	5.6	26.5	29.1	16.2	8.1	5.5
Natural Gas	18.3	13.3	7.1	8.0	5.0	18.4	14.8	15.0	11.7	7.9
RBOB Gasoline	28.8	22.5	7.3	6.8	7.8	28.8	30.1	15.6	9.4	6.2
Silver	8.6	5.4	5.5	5.3	5.3	8.8	7.0	5.5	4.8	5.4
Sugar	8.6	5.4	4.4	3.9	3.7	8.6	6.4	5.3	3.8	3.6
West Texas Crude Oil	6.9	3.2	2.5	2.6	2.6	7.0	4.0	3.1	2.2	2.2

Table 12 contains the transaction costs (in basis points) for a trader who has $1,000,000 worth of a commodity to trade. In the 5-minute scenario, they trade the amount available at the best bid or ask, then wait five minutes and trade the remainder. In the 10-minute scenario, they trade the amount available at the best bid or ask, then wait five minutes and trade what is available at the best bid or ask and trade the remainder five minutes later. The transaction costs are calculated as the relative difference between the midpoint at the time of the first trade and the weighted average execution price. This analysis is repeated each hour in August 2009. The 100% (50%) depth results are based on the assumption that 100% (50%) of depth has been restored five minutes after the trade.

is an estimate, we generate results based on the assumption that (a) just 50% of level 1 depth is restored after five minutes; and (b) 100% of depth is restored after five minutes.

The five-minute results assume a trader executes what they can at the best bid or ask quote and then waits five minutes to execute the remainder. If there is not sufficient depth at the best bid or ask price at that point, they are assumed to walk the book so their trade is fully executed. Under the ten-minute results, a trader is assumed to execute what they can at the first level of the book, wait five minutes and execute what they can at that point (at level 1 of the book), and then transact the remainder after ten minutes. Transaction costs are calculated as the relative difference between the midpoint at the time of the first trade and the weighted average transaction price.

The results in Table 12 indicate that patient traders do experience lower transaction costs. Traders who execute what is available at the first level of the book and the remainder five minutes later experience average transaction costs of 25.1 to 25.2 basis points, compared to 25.8 basis points on average for $1,000,000 trades executed immediately. The more patient the trader, the bigger the reduction in execution costs, as less of the trade walks the book. Waiting 30 minutes leads to average transaction costs in the 10.0 to 15.3 basis point range, while waiting 60 minutes results in average transaction costs of 6.5 to 8.6 basis points. Being patient and splitting trades multiple times leads to

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greater reductions in transaction costs in the less liquid commodities like coffee than the more liquid commodities such as West Texas crude oil. Delaying complete execution of trades results in execution price volatility. However, the results reported in Table 12 are after this has been accounted for. This clearly does not subsume the benefits of trade splitting.

5. Conclusion

Liquidity is a critical component of many studies in finance, so it is not surprising that many liquidity proxies have been developed using daily data. The accuracy of these proxies in equity markets is well known, but little is known about their precision for commodities. This article investigates this issue. We find that the Amihud measure has the largest correlation with commodity transaction costs. The Amivest and Effective Tick proxies also perform well. A researcher in an area such as asset pricing who has volume data should use Amihud or all three of these measures. A researcher who does not have volume data should use the Effective Tick measure.

The scale of a liquidity proxy compared to a liquidity benchmark is just as important as its correlation with that benchmark to researchers in areas such as market efficiency and to practitioners. None of the liquidity proxies accurately reflect the scale of actual transaction costs in commodities. We document actual transaction costs for different trade sizes under a range of scenarios, such as when investors are prepared to wait for different lengths of time to complete their trades and when they require immediate execution.

For trades that can be fully executed at the first level of the book, half spreads range from 3.5 to 4.4 basis points. Traders who demand immediacy experience larger costs. Small trades executed immediately incur an average cost of 6.3 basis points, which is greater than the average half quoted spread of 5.1 basis points 45% of the time. Large trades executed immediately require a trader to “walk the book” 95% of the time and have an average cost of 25.8 basis points. Commodity liquidity is highly resilient. In excess of 70% of depth has been restored five minutes after a trade, and liquidity has been fully restored, on average, between 30 and 60 minutes after a trade. Investors can reduce trading costs by splitting their trades, with more patient traders receiving a larger benefit. Traders who are prepared to execute a $1,000,000 trade over 60 minutes experience costs of 6.5 to 8.6 basis points, on average, which are considerably lower than trading costs for the same-sized trade executed immediately. Commodities from the energy and precious metals families have lower average trading costs than commodities from the livestock and agricultural families. However, there is variation within commodity families. For instance, soybeans have relatively low transaction costs. Similar to other empirical research, our results need to be qualified given that our data period is relatively short in some instances, but we hope they provide researchers into commodity liquidity and transaction costs with useful information.

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Table A1
Appendix 1: Price impact correlations by trade size

Trade size		Roll Impact	Eff Tick Impact	Gibbs Impact	Zeros Impact	Zeros2 Impact	High-Low Impact	FHT Impact	PS	Amihud	Amivest
Small	Correlation	0.130	0.362	0.382	0.040	0.069	0.295	0.047	−0.041	0.400	−0.365
	p-Value	0.009	0.000	0.000	0.186	0.015	0.000	0.150	0.276	0.000	0.000
Medium	Correlation	0.148	0.421	0.396	0.083	0.106	0.376	0.084	−0.102	0.446	−0.392
	p-Value	0.001	0.000	0.000	0.008	0.000	0.000	0.007	0.029	0.000	0.000
Large	Correlation	0.118	0.333	0.382	0.084	0.091	0.296	0.085	−0.105	0.386	−0.344
	p-Value	0.014	0.000	0.000	0.057	0.029	0.000	0.060	0.014	0.000	0.000

Appendix 1 contains the cross-sectional average Spearman correlation coefficients between the price-impact benchmark and the price-impact proxies by trade size. Small, medium, and large refer to the smallest third, middle third, and largest third of trade sizes. * indicates that the null hypothesis, that the smallest and largest trade size correlations for each proxy are the same, can be rejected at the 10% level.

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Table A2
Appendix 2: Quoted spread correlations by year

	Roll	Eff Tick	Gibbs	Zeros	Zeros2	High-Low	FHT	Amihud	Amivest
1996	−0.05	0.16	0.14	0.12	0.09	0.23	0.16	0.30	−0.23
1997	−0.09	0.13	0.14	0.08	0.13	−0.10	0.10	0.26	−0.12
1998	0.21	0.13	0.21	−0.18	−0.20	0.21	−0.09	0.38	−0.21
1999	−0.07	0.27	0.30	−0.03	−0.06	0.35	0.01	0.29	−0.23
2000	0.01	0.23	0.08	−0.05	−0.08	0.11	0.04	0.24	−0.18
2001	0.06	0.20	0.20	−0.02	−0.02	0.20	−0.03	0.47	−0.34
2002	0.12	0.35	0.13	−0.09	−0.24	0.06	−0.11	0.47	−0.36
2003	0.02	0.10	0.34	0.07	0.03	0.07	0.08	0.26	−0.19
2004	0.00	0.31	0.20	0.12	0.04	0.13	0.11	0.34	−0.21
2005	0.00	0.24	0.24	0.11	0.09	−0.07	0.10	0.39	−0.23
2006	−0.12	−0.06	−0.05	−0.12	−0.08	−0.05	−0.11	0.34	−0.28
2007	0.18	0.30	0.17	0.18	−0.01	0.09	0.20	0.39	−0.23
2008	0.23	0.28	0.31	0.04	−0.03	0.29	0.16	0.62	−0.42
2009	−0.05	0.25	0.21	0.18	0.04	0.22	0.18	0.77	−0.51

Appendix 2 contains quoted spread correlations by year. The sample period commences in 1996, or whenever each commodity’s data commence, and ends in August 2009.

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Table A3
Appendix 3: Price impact by trade size

	(0, 100k]	(100k, 200k]	(200k, 300k]	(300k, 400k]	(400k, 500k]	(500k, 600k]	(600k, 700k]	(700k, 800k]	(800k, 900k]	900k+
Panel A: All and by family										
All	2.5	2.8	3.0	3.3	3.5	3.6	3.7	3.8	3.8	4.2
Energy	2.3	2.0	2.2	2.3	2.4	2.4	2.4	2.6	2.6	2.7
Precious Metal	1.2	1.5	1.6	1.7	1.8	1.8	1.9	1.9	1.8	2.3
Livestock	3.5	4.0	4.3	4.7	5.1	5.2	5.6	4.9	5.5	6.2
Agricultural	2.7	3.2	3.5	3.8	4.2	4.3	4.4	4.7	4.6	5.2
Panel B: By commodity										
Brent Crude Oil	1.9	1.6	1.6	1.7	1.7	1.6	1.7	1.8	1.6	1.6
Cocoa	4.0	4.4	4.6	5.3	5.7	5.5	4.2	6.6	5.3	6.1
Coffee	2.4	3.0	3.0	3.8	3.4	3.6	5.1	4.7	4.3	4.0
Corn	1.7	2.3	2.6	2.8	3.1	3.2	2.9	3.1	3.5	3.9
Cotton	3.5	3.9	4.6	4.3	5.3	4.7	5.5	4.9	4.3	5.1
Feeder Cattle	4.9	5.3	5.6	6.1	6.3	6.8	7.1	6.0	6.3	8.9
Gasoil	2.5	2.2	2.4	2.3	2.2	2.5	2.4	2.7	2.8	2.4
Gold	0.7	0.9	1.0	1.0	1.0	1.1	1.2	1.2	1.2	1.4
Heating Oil	2.6	2.2	2.5	2.3	2.6	2.6	2.5	2.9	2.5	3.0
Lean Hogs	3.5	4.2	4.5	5.1	5.3	5.2	6.1	5.2	6.6	5.4
Live Cattle	2.1	2.6	3.0	3.0	3.7	3.6	3.6	3.5	3.7	4.4
Natural Gas	2.6	2.4	2.7	3.2	3.3	3.2	3.3	3.3	3.8	4.0
RBOB Gasoline	2.6	2.3	2.7	2.6	2.7	2.9	2.8	3.2	3.1	3.1
Red Wheat	3.8	4.2	4.5	5.1	5.4	6.1	6.2	6.6	7.5	8.5
Silver	1.7	2.1	2.3	2.4	2.6	2.5	2.7	2.6	2.4	3.3
Soybeans	1.4	1.7	1.8	1.9	2.0	2.1	2.2	2.3	2.6	2.7
Sugar	2.5	3.4	3.8	4.0	4.4	4.9	4.3	4.7	5.4	5.7
West Texas Crude Oil	1.7	1.6	1.7	1.9	1.9	2.0	1.9	2.1	2.2	2.3
Wheat	2.4	3.1	3.5	3.7	4.1	4.3	4.6	4.5	4.5	5.4

This appendix contains mean effective one-way price impact measures for different dollar value trade size buckets. The sample period commences in April 2008 and ends in August 2009. Results are reported in basis points.

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Table A4
Appendix 4: Effective half spread and volatility

	Average effective half spread					Average volatility				
	Low	2	3	4	High	Low	2	3	4	High
Brent Crude Oil	1.8	1.8	1.9	2.5	2.9	7.1	10.2	13.0	17.6	26.2
Cocoa	4.7	5.1	5.4	5.8	6.6	8.6	10.7	12.3	14.1	17.7
Coffee	3.5	3.6	3.8	4.0	5.2	7.3	8.9	9.9	11.3	14.4
Corn	3.8	4.1	4.4	4.7	5.0	5.5	7.8	9.6	11.7	16.3
Cotton	4.0	4.5	4.9	5.2	6.8	7.5	9.4	11.0	12.9	18.9
Feeder Cattle	4.3	5.4	7.4	8.4	9.7	4.5	5.9	7.5	9.1	12.4
Gasoil	2.5	2.6	2.8	3.3	3.7	8.5	11.1	13.5	17.2	23.5
Gold	0.9	1.0	1.3	1.5	2.0	3.1	5.1	7.2	9.4	15.0
Heating Oil	2.8	3.1	3.6	4.6	5.3	8.4	11.6	14.1	17.8	23.9
Lean Hogs	4.6	4.9	5.3	5.5	5.8	5.7	7.0	8.1	9.6	13.0
Live Cattle	2.9	3.1	3.4	3.7	4.3	3.5	4.4	5.2	6.2	8.6
Natural Gas	4.1	4.2	4.4	4.5	4.6	8.2	11.9	14.8	17.7	22.7
RBOB Gasoline	3.3	3.7	4.3	6.3	8.5	8.6	11.9	14.7	19.9	29.9
Red Wheat	4.3	4.5	4.7	4.8	5.1	9.1	11.2	12.8	14.8	19.5
Silver	3.2	3.1	3.0	3.5	5.4	5.7	7.9	10.2	13.0	23.0
Soybeans	2.8	2.9	2.9	3.1	3.4	5.3	7.3	8.9	10.9	14.8
Sugar	4.0	4.2	4.4	4.5	4.5	8.7	10.8	12.4	14.2	17.4
West Texas Crude Oil	1.4	1.8	1.9	2.3	2.7	5.1	8.4	11.5	15.1	24.6
Wheat	4.5	4.7	4.7	4.8	5.2	7.0	9.1	10.8	12.7	16.7

Appendix 4 presents the average effective half spreads and average volatilities in basis points for volatility quintiles. Moving average volatilities, based on a 5-minute window of 120 absolute changes in the midpoint, are calculated for each commodity. These volatilities are ranked into quintiles. Average effective half spread and average volatility level are then calculated for each volatility quintile. The sample period is April 2008 until August 2009.

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