Traces of Humanity: Liquidity and Human Behavior in the Machine Age*

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Abstract: Machines dominate trading in modern markets, and some observers may assume that human behavior no longer affects liquidity generation and consumption. Our research challenges this view. Liquidity costs follow strong behavioral patterns, with costs highest in early winter and lowest in late spring, a 5.7% difference driven by changes in risk aversion and impatience that correlate with seasonal changes in daylight exposure. As informed traders become more impatient from late summer to early winter, they generate more adverse selection, while liquidity providers demand higher compensation as they become more risk-averse. Together these patterns drive liquidity costs up and down annually.

Key words: time-varying liquidity, adverse selection, seasonal behavioral effects

JEL: G14; G15

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1. Introduction

Trading in modern markets is generally run by algorithms. A common view is to think of such algorithms as devoid of emotion or feeling, and people's perceptions of modern markets tend to be influenced by this thinking. The literature shows that automation has improved many aspects of trading and investing, from market maker attention deficits to portfolio selection. The question that remains is: With algorithms playing such a significant role, do any traces of human nature remain in the way liquidity is generated and consumed? If so, to what extent? After all, people design, parameterize, calibrate, and recalibrate the algorithms. We report evidence that liquidity provision and consumption display large, economically relevant patterns undetected in previous work. Furthermore, we offer a behavioral rationale for these trends, which is bolstered by research in both psychology and economics.

Theory dating back to Stoll (1978) and Ho and Stoll (1981, 1983) suggests that the magnitude of spreads is determined in part by the risk aversion of market makers, the individuals that are tasked with writing and maintaining the algorithms that underlie most trading activity. We analyze liquidity over the past decade and find that human nature has predictable effects even though algorithms are a pervasive feature of modern trading. Specifically, there exists significant variation in a number of standard liquidity measures that appears to be related to variation in human mood.

In our primary analysis, we find a large and significant regularity in the bid-ask spreads of U.S.-listed firms. Quoted spreads vary by 5.7% over the year, widening from late summer to peak in December, then narrowing to their nadir in the spring. This variation surpasses by more than two-fold the recently reported spread changes due to new trading technologies such as colocation and microwave transmission (e.g., Brogaard, Hagströmer, Nordén, and Riordan (2015) and Shkilko and Sokolov (2020)). Making use of high frequency metrics that reflect changes in adverse selection, liquidity providers' inventory costs, fixed costs, and revenues, we further identify seasonal variation in the demand for immediacy (loosely speaking, impatience) of informed traders and the appetite for risk bearing by the providers of liquidity. Identification of this behavioural source of spreads seasonality is aided by robustness checks based on liquidity data from countries around the globe and is consistent with market participants experiencing seasonally varying risk aversion and impatience, even after controlling for known determinants of spreads.

While much variation in risk aversion is idiosyncratic and unlikely to impact markets systematically, there is one systematic source of variation in market participants' risk aversion that synchronizes large swaths of the population, indiscriminately impacting the rich and the poor. As much as ten percent of the world population suffers from seasonal depression (or seasonal affective disorder; SAD) during the fall and winter, with most of the remainder experiencing a milder analogue, winter blues (see Kamstra, Kramer, and Levi (2003) and Kramer and Weber (2012)). Onset of seasonal depression is typically in the fall, recovery is typically in the spring, and it is well accepted by medical professionals that the primary cause of the seasonal variation is a reduction in hours daylight, as opposed to other environmental variables such as rainfall or cloud cover; see Young, Meaden, Fogg, Cherin, and Eastman (1997).

Seasonality in depression is, in turn, associated with seasonality in risk aversion and impatience. Consider first risk aversion: a number of studies in economics and psychology find that depressed individuals are more risk averse. For instance, see Pietromonaco and Rook (1987), Harlow and Brown (1990), Wong and Carducci (1991) Carton, Jouvent, Bungener, and Widlöcher (1992), Carton, Morand, Bungenera, and Jouvent (1995), and Smoski, Lynch, Rosenthal, Cheavens, Chapman, and Krishnan (2008). Exploiting a panel of participants over time in an incentive-compatible risky financial choice setting, Kramer and Weber (2012) find people with seasonally varying depression exhibit seasonally varying risk aversion. Kamstra, Kramer, and Levi (2003, 2012) examine Treasury security returns and stock returns and find statistically significant, economically large seasonal patterns consistent with seasonal-depression-driven changes in market participants' risk aversion. Kamstra, Kramer, Levi, and Wermers (2017) find seasonal variation in investor fund flows in and out of risky versus safe categories of mutual fund flows are consistent with seasonally varying risk aversion.

Consider next impatience. A variety of studies, including experimental and neuroimaging studies, find that depressed people are more impatient on average; see Pulcu, Trotter, Thomas, McFarquhar, Sahakian, Deakin, Zahn, Anderson, and Elliott (2014), Ludwig, Nüsser, Goschke, Wittfoth-Schardt, Wiers, Erk, Schott, and Walter (2015), and Amlung, Marsden, Holshausen, Morris, Patel, Vedelago, Naish, Reed, and McCabe (2019). In contrast to risk aversion, few studies in finance have explored the implications of time variation in impatience. One paper that has done so, by Kamstra, Kramer, Levi, and Wang (2014), shows in a representative agent equilibrium asset pricing model framework that seasonal variation in both impatience and risk aversion is necessary to match observed (quarterly) seasonality in equity and Treasury returns.

The identification of seasonality in depression as a key determinant of seasonality in spreads relies on several separate pieces of evidence. First, we find that spreads are correlated over time with the clinical timing of SAD symptoms. Second, we find that the seasonality of spreads in the international cross section varies with latitude.[1] The most northern countries exhibit the largest seasonal variation in spreads, countries in the north subtropics exhibit relatively smaller variation, and countries located in the tropics exhibit exhibit virtually no seasonal variation. Third, just as the seasons are shifted by six months in the southern hemisphere, so is the seasonal pattern in spreads. Finally, the seasonality in spreads we document is larger for smaller firms – firms which are riskier to trade by both liquidity providers and demanders – consistent with time variation in risk aversion impacting assets that vary in riskiness differently.

Our findings may appear surprising in light of the dominance of algorithmic trading in modern markets. In fact, while the use of machines is certainly widespread and pervasive, the influ-

[1]Because seasonal variation in light exposure is a key determinant of seasonality in depression, risk aversion, and impatience, several studies of financial market seasonality exploit variation in hours of daylight across different geographic latitudes in their empirical tests. These studies tend to find stronger seasonal variation in economic quantities the higher the latitude of the market.

ence of humans remains important. For example, even the most tech-savvy trading firms rely on humans to set trading model parameters and calibrate liquidity-making and liquidity-taking algorithms. In addition, humans periodically override system defaults. These interventions provide ample opportunity for human behavior to continue to exert a significant influence on liquidity generation and consumption, even in the age of machines.

2. Data, sample, and metrics

Our data come from three sources. First, we use the Trade and Quote (TAQ) database to compute high-frequency intraday liquidity metrics for U.S. firms. These metrics include the quoted, effective, and realized spreads as well as price impacts. Second, we use Datastream to compute the low-frequency alternatives to the TAQ quoted and effective spreads. These are discussed by Corwin and Schultz (2012) and Abdi and Ranaldo (2017).[2] The low-frequency metrics allow us to expand the analyses to several non-U.S. markets, for which we do not have intraday data. In turn, these markets let us examine variation in SAD onset patterns and severity as they vary across geographic latitudes. Finally, to compute market capitalization, returns, and volatility for the U.S. sample, we use data from the Center for Research in Security Prices (CRSP).

The sample period spans ten years, from 2010 through 2019. During this span of time, automation determines much of how financial markets function, and therefore this period provides a unique laboratory for asking our main question: Does human behavior affect liquidity in the machine age? When selecting the sample of U.S. firms, we begin with 1,000 largest firms traded on the largest U.S. exchange, NYSE, as of January 2010 and drop those for which prices fall below $5 or rise above $500 at any time during the sample period. This procedure leaves us with the final sample of 939 firms.

[2] Corwin and Schultz (2012) observe that an advantage of their spread estimator is its suitability for use across different markets with different market structures, which is useful in our context where we study spreads from countries around the world.

2.1 Market quality metrics

In the analysis of the U.S. sample, we rely on conventional high-frequency metrics of displayed liquidity and trading costs. First, to examine displayed liquidity, we estimate the *quoted spread* as the difference between the best offer and the best bid. Second, to measure trading costs incurred by the liquidity demanders, we compute the *effective spread* as twice the signed difference between the traded price and the quote midpoint at the time of the trade. Next, to assess the levels of adverse selection, we compute the *price impact* as twice the signed difference between the quote midpoint at the time of the trade and the midpoint 60 or 300 seconds after the trade. We vary the price impact horizons between 60 and 300 seconds to account for the lower frequency of trading in the smaller stocks. While the 60-second horizon may be suitable for the frequently traded stocks, the 300-second horizon may be more optimal for their less frequently traded counterparts. Finally, to examine liquidity provider inventory costs, fixed costs, and revenues we follow Hendershott and Moulton (2011) and Brogaard, Hagströmer, Nordén, and Riordan (2015) and use the *realized spread*, which is the difference between the effective spread and price impact.

Price impacts are a particularly important metric for our analyses because they capture impatience of informed investors. Such investors may act on price-relevant information by submitting marketable or non-marketable limit orders (e.g., O'Hara (2015), Bhattacharya and Saar (2020)). Marketable orders consume liquidity that is on offer and therefore have a greater probability of execution and greater execution speed, and impatient informed traders prefer using them over non-marketable limit orders. The price impact metric in turn captures the extent to which marketable orders move prices. As such, we build our discussion on the premise that if the share of impatient informed trading increases, so will the price impact.

Behavioral changes in market-participant patience is an as-yet unexplored angle in the market structure literature. In the meantime, the literature proposes several non-behavioral reasons for informed trader impatience. These include (i) competition among traders whose information is homogeneous (Holden and Subrahmanyam (1992)), (ii) high information value that raises the opportunity costs of non-execution (Kaniel and Liu (2006)), and (iii) uncertainty of information revelation timing that increases the risk of information becoming public before an informed trader may act on it (Chau and Vayanos (2008)). We believe that these determinants of impatience are unlikely to change seasonally. It is difficult to imagine why, for instance, each year informed traders would obtain more valuable information in October and November as compared to April and May, or that such information would be more homogeneous and incite more competition.

When computing the high-frequency metrics, we follow the procedure suggested by Holden and Jacobsen (2014) and use the Lee and Ready (1991) algorithm to sign trades. Chakrabarty, Pascual, and Shkilko (2015) show that the algorithm performs well in modern markets. All high-frequency metrics are scaled by the corresponding quote midpoints. We also drop the first and last five minutes of the trading day to reduce the effects of the opening and closing procedures.

Table 1 contains sample summary statistics. The average stock has market capitalization of $14.3 billion and trades at $51.02 per share. The average daily volume of shares traded is nearly 2.5 million. There is a notable variability across sample stocks as should be expected from a sample of over 900 equities, with market capitalization ranging between $2.7 billion in the 25^{th} percentile and $13.3 billion in the 75^{th} percentile. Prices and share volumes exhibit similar variations.

[Table 1]

When it comes to high-frequency liquidity metrics, we find that the average quoted spread is 7.42 bps, while the average effective spread is 5.77 bps. The effective spread captures trading costs incurred by traders who take liquidity. It is usually smaller than the quoted spread, because liquidity takers often come to the market when liquidity is cheaper and may also receive price improvement relative to the displayed quotes. In turn, the average 60-second price impact is 4.24

bps and increases to 4.58 bps when we extend the measurement horizon to 300 seconds. This result is expected, as information often drifts into prices for some time after the trade (Conrad and Wahal (2020)). Finally, the average realized spread is 1.51 bps at the 60-second horizon and 1.17 bps at the 300-second horizon. Similarly to stock characteristics, there is a non-trivial cross-sectional variation in liquidity metrics. In a later section, we explore this variation by examining the results in the cross-section.

The bottom portion of Table 1 reports three low-frequency liquidity metrics for the U.S. sample. In a later section, we show that these metrics reveal SAD effects as successfully as do the high-frequency metrics, allowing us to expand the analysis to non-U.S. markets. The three metrics are (i) the quoted spread computed using the end-of-day CRSP quotes, *EOD*, and (ii) and (iii) the effective spread estimators proposed by Corwin and Schultz (2012) and Abdi and Ranaldo (2017), respectively, *CS* and *AR*. Abdi and Ranaldo (2017) show that the *EOD* quoted spread is the most accurate low-frequency liquidity proxy. Since our high-frequency metrics distinguish between quoted and effective spreads, we supplement *EOD* with *CS* and *AR* for comparability.

Jahan-Parvar and Zikes (2022) show that *CS* and *AR* often produce estimates that are considerably larger than the high-frequency estimates. The data lead us to the same conclusion. While the *EOD* quoted spread is close in magnitude to its high-frequency counterpart (i.e., 6.14 bps compared to 7.42 bps), the *CS* and *AR* estimates are 96.83 and 128.52 bps. We note that the magnitudes of the estimates are not as important for our analyses as their ability to capture changes in liquidity costs over time. As we show in a later section, for this purpose both *CS* and *AR* work rather well.

2.2 The Seasonal Affective Disorder metrics

We employ two primary measures related to SAD in this analysis: SAD Incidence and SAD Onset/Recovery; we refer to the sum of these measures as SAD Composite. We use Incidence to proxy for market maker risk aversion, and we use Onset/Recovery as a metric for trader impatience.

2.2.1 SAD Incidence. To create the SAD Incidence variable, which we use to model the seasonal pattern in market participant risk aversion, we adopt a measure of seasonality based on the clinical timing of SAD symptoms among people who experience seasonal depression, as developed by Kamstra, Kramer, and Levi (2015). Young, Meaden, Fogg, Cherin, and Eastman (1997) and Lam (1998) conducted studies of hundreds of SAD patients in North American and recorded the date when each patient's SAD symptoms first arose in the late summer or fall and the date when their symptoms dissipated. We use the data sets made available by them to create a proxy for the timing of seasonal changes in risk aversion among those who are affected by SAD.

Specifically, we calculate the fraction of people susceptible to SAD who are actively exhibiting SAD symptoms in a given month. Starting in late summer, the earliest point of the year when symptoms first appear for SAD patients, we calculate the monthly cumulative proportion of people actively experiencing SAD net of the monthly proportion of people who have recovered.

Then we employ a spline function to smoothly interpolate that monthly variable to daily frequency, resulting in our daily measure of SAD Incidence. The value of SAD incidence is zero in summer, when virtually no one experiences SAD symptoms. It increases most rapidly around fall equinox in mid-September when hours of daylight are diminishing most rapidly, and the proportion of SAD-suffers experiencing the start of their symptoms is very high. SAD incidence peaks near 100% in winter, reflecting the fact that close to 100% of the people who are prone to suffer from SAD have begun experiencing their symptoms by the time winter begins. Finally the measure decreases most rapidly around spring equinox in March, when hours of daylight are increasing most rapidly, and the proportion of SAD-suffers recovering is very high, and reaches a low of zero again the subsequent summer.

The SAD Incidence variable reflects the *stock* of people who are actively experiencing SAD symptoms, including heightened risk aversion, and so we use SAD Incidence as a proxy for seasonally varying market maker risk aversion. Because this proxy measures the true incidence of SAD with error, using it directly could impart an errors-in-variables bias. Thus we follow Kamstra, Kramer, Levi, and Wermers (2017) and use an instrumented version of the proxy.[3]

2.2.2 SAD Onset/Recovery. To create a proxy for seasonally varying trader impatience, we consider the *net flow* of people becoming affected by or recovering from SAD – i.e., the change in the proportion of people actively experiencing symptoms – resulting in the SAD Onset/Recovery variable. We compute this measure by calculating the change in the value of the SAD Incidence variable. SAD Onset/Recovery takes on its highest (positive) value around fall equinox, the point in time when the rate at which SAD-suffers are first experiencing their symptoms is highest. SAD Onset/Recovery takes on its lowest (negative) value around spring equinox, when the rate of recovery from SAD is highest. We hypothesize that trader impatience peaks around September and troughs around March, at the two extreme points of the Onset/Recovery cycle.

2.2.3 SAD Composite. Summing SAD Incidence and SAD Onset/Recovery yields the SAD Composite variable, intended to capture the combined effects of seasonally varying risk aversion and seasonally varying impatience.

3. Empirical results

3.1 High-frequency liquidity metrics

Increased impatience and risk aversion associated with SAD may affect market participants in two ways. First, upon becoming more impatient, informed traders may use more marketable

[3] We produce the instrumented version of SAD Incidence as follows. First, we use a spline function to smoothly interpolate the monthly SAD Incidence variable to daily frequency. Then we run a logistic regression of the daily SAD Incidence measure on length of day. The fitted value from this regression yields the instrumented version of SAD Incidence.

orders, and adverse selection of liquidity provider quotes may increase as a result. Second, liquidity providers may require additional compensation for assuming inventory risk due to increased risk aversion. Both of these phenomena should lead to greater liquidity costs.

Figure 1 explores initial support for these possibilities by plotting monthly estimates of realized spreads and price impact against the appropriate measures of SAD. Note that to facilitate comparison across plots, we demean each series we plot. Thus spread values above zero represent cases above the series average and vice versa. Consider the top two plots first, showing realized spreads which are calculated as the difference between effective spreads and price impacts and as such represent the difference between liquidity providers' revenues and their adverse selection costs. We hypothesize that realized spreads widen during periods when liquidity providers are more risk averse, and accordingly we plot realized spreads against SAD Incidence. Realized spreads appear in green (light green for 60s and darker green for 300s), the long-dashed line is SAD Incidence (scaled to match the magnitude of the plotted spreads), and dotted lines show a 90% confidence interval around the spreads, based on a regression model detailed later in this section.

[Figure 1]

In both plots, realized spreads are visibly correlated with SAD Incidence, decreasing through late winter and spring then increasing in late summer to reach peak levels in the late fall/early winter. These patterns approximate the seasonal hours of darkness in the northern hemisphere and the timing of seasonal risk aversion captured by SAD Incidence. We note that the economic effects of these changes are nontrivial, for example with the 60-second realized spreads increasing about 0.16 bps from the spring lows to late autumn highs, representing 10.5% (=0.16/1.51) of the unconditional mean realized spread.

The two bottom plots appearing in Figure 1 correspond to price impact. Here the 60-second price impact appears in light blue on the left and 300-second in darker blue on the right. We expect price impact to reflect the impatience of informed traders, which we hypothesize will be captured by SAD Onset/Recovery represented by the long-dashed line. The economic magnitude of the seasonal change is again large, with a 0.21 bps difference between the spring low and the autumn high values of the 60-second price impact, representing a seasonal change of 4.9% (=0.21/4.24).

Figure 2 provides similar glimpses of the data for the effective spread (top plot) and quoted spread (bottom plot). Because these spreads reflect the combined effects of market participants' risk aversion and impatience, we plot them against the SAD Composite variable. The magnitude of the 0.26 bps seasonal variation in the effective spread represents variation of 4.4% (=0.26/5.77) relative to the mean effective spread, and the seasonal change in the quoted spread, 0.42 bps, represents a 5.7% (=0.42/7.42) difference relative to the mean quoted spread.

[Figure 2]

Whereas the results in Figures 1 and 2 are suggestive of a seasonal connection between SAD and spreads, they do not account for the well-known trading cost determinants such as volume and volatility. To address this issue, we conduct more formal analysis by estimating the following regression model for each stock i on each day t:

$$DepVar_{i,t} = \alpha_i + \gamma_{year} + \beta_1 SAD_t + \beta_2 Volume_{i,t-1} + \beta_3 Volatility_{i,t-1} + \varepsilon_{i,t}, \tag{1}$$

where $DepVar$ is the quoted spread, effective spread, price impact, or realized spread, SAD is a place-holder for the appropriate SAD proxy (SAD Incidence, SAD Onset/Recovery, or SAD Composite), $Volume$ is the lagged natural logarithm of daily volume, and $Volatility$ is the lagged difference between the highest and lowest price of the day scaled by the average of the two prices and multiplied by 100. We estimate this model using ordinary least squares, controlling for stock and year fixed effects, and clustering the standard errors by firm and date.

The results in Table 2 are consistent with our expectations, in that both quoted and effective spreads vary with the SAD Composite variable, which captures the effects of both risk aversion and impatience, both of which we hypothesize influence quoted and effective spreads. The quoted spreads increase by 0.399 bps and the effective spreads increase by 0.243 bps in Base regressions (columns [1] and [3]); estimates are similar in Full regressions that control for the effects of volume and volatility (columns [2] and [4]). We note that the economic magnitude of these changes is consistent with that observed in univariate results, albeit it is more moderate likely due to controlling for the spread determinants. Specifically, quoted spreads vary by 6.0% (=0.399x1.11/7.42) and effective spreads by 4.7% (=0.243x1.11/5.77).[4] The coefficient estimates on the SAD variable are all strongly statistically significant, with t-tests generally over five.

[Table 2]

Next we use the regression setting to examine the components of the effective spread: price impacts and realized spreads. We expect price impact to capture the effects of informed trader impatience, and we expect realized spreads to capture liquidity providers' risk aversion; hence we use the SAD Onset/Recovery variable and the SAD Incidence variable respectively to capture seasonality. The results are consistent with our expectations; both price impacts and realized spreads increase with the relevant SAD measure. In Panel A, the price impacts measured at the 60-second horizons increase by 0.325 bps and those measured at 300-second horizons increase by 0.363 bps in the Base models in columns [1] and [3]. This translates into an economically large seasonal variation of 7.4% (=0.325x0.786/4.24, accounting for the 0.786 range of the SAD Onset/Recovery variable) for the 60-second case and 6.2% (=0.363x0.786/4.58) for the 300-second case. Results are similar in specifications [2] and [4] which control for volatility and volume. These results are consistent with the notion that when the value of the SAD Onset/Recovery vari-

[4] The economic magnitudes are calculated as the coefficient estimate times the range of the SAD variable (roughly 1.1 in the case of SAD Composite) divided by the mean spread value from Table 1.

able is high, informed trader impatience increases, and they tilt their order submission mix to marketable orders. These orders in turn increase adverse selection of liquidity provider quotes.

In Panel B, the 60-second realized spreads increase by 0.118 bps and the 300-second realized spreads increase by 0.116 bps in the Base models (and increase similarly in specifications [2] and [4]). These results are consistent with the notion that risk aversion is directly related to SAD Incidence thereby increasing compensation that liquidity providers expect to obtain for holding inventory and committing capital. Again, the coefficient estimates on the SAD variable are all strongly statistically significant, and the economic magnitudes are large. For the 60-second realized spread, the seasonal variation relative to the mean amounts to 7.4% (=0.118x0.944/1.51, based on the 0.944 range of the SAD Incidence variable), and for the 300-second realized spread, the economic magnitude is 9.4% (=0.166x0.944/1.17).

[Table 3]

3.2 Low-frequency liquidity metrics

In a later section we expand our analysis to international markets because the magnitude of the SAD effect, as well as its seasonality, should exhibit considerable variation across geographic locations. Specifically, the extent of seasonal depression varies by latitude. Locations closer to the equator receive less variable amounts of light exposure during the year and therefore people living in such locations experience SAD symptoms to a lesser extent. Also, the timing of the SAD cycle in countries located in the Southern Hemisphere is six months removed from that in the Northern Hemisphere. These variations allow us to verify if the effects documented in the United States extend to other jurisdictions and to confirm that they are less likely to be driven by confounding factors.

For the international markets we lack high-frequency data so we must instead resort to the low-frequency liquidity proxies. These include the end-of-day (EOD) quoted spreads, the

Corwin-Schultz (CS) effective spread estimator, and also the Abdi-Ranaldo (AR) effective spread estimator. Abdi and Ranaldo (2017) show that when the quote data are available, the EOD spreads are the most reflective of liquidity conditions. Even though these low-frequency estimators have been shown to work in previous research, we would like to test whether they pick up the same seasonal patterns as those picked up by the high-frequency metrics. To do so, in this section we repeat the earlier analyses using the low-frequency metrics.

We begin with a visual. Figure 3 shows that seasonal correlations between the low-frequency metrics and the SAD Composite variable closely resemble those identified earlier for the high-frequency spread metric. That is, both the low-frequency metrics and the SAD Composite variable dip in late spring and peak in late fall. And the magnitude of the seasonal change are again large: 0.71 bps (or 11.6%=0.71/6.14 relative to the unconditional mean) for the end-of-day quotes, 5.34 bps (5.5%=5.34/96.83 relative to the unconditional mean) for the Corwin-Schultz spreads, and 8.58 bps (6.5%=8.58/128.52 relative to the unconditional mean) for the Abdi-Ranaldo spreads. In turn, the equation (1) results in Table 4 confirm that all three proxies vary with the SAD Composite variable. The SAD coefficient is strongly statistically significant for the EOD and CS spreads, while the SAD coefficient is insignificant for the AR spread. Due to dropping negative spread estimates for the AR method we have only a third as many observations for AR compared to the EOD case, a shortfall which may explain our lack of power to identify the SAD effect here. Altogether, it appears that both the high-frequency and the low-frequency proxies are sufficiently sensitive to identify the seasonal relations between liquidity costs and SAD.

[Figure 3, Table 4]

3.3 Cross-sectional analysis

To explore cross-sectional differences in the U.S. data, we split our sample into three groups on the basis of firm size, re-sorted daily based on the previous day's market capitalization. Tercile 1 contains the largest firms. Summary statistics appear in Table 5. The largest group of firms has a mean size above $27 billion, and the smallest $2.4 billion. The high- and low-frequency liquidity cost metrics are consistently smallest for tercile 1 and increase as firm size decreases.

[Table 5]

We examine the relationship between SAD and the various liquidity metrics for each of the terciles in Tables 6 and 7. Price impact and realized spreads appear in Table 6. Price impact increases more with SAD for small firms than for large firms. Turning to the realized spreads measured at 60-second horizons, they increase 0.042 bps, 0.120 bps, and 0.223 bps for the large through small terciles, respectively, with similar figures for the 300-second horizons. In all cases, the statistical significance of the SAD coefficient remains very high, with *t*-tests no lower than 3.

[Table 6]

Table 7 contains regression results for the high-frequency quoted and effective spreads, the low-frequency end-of-day quoted spreads, Corwin-Schultz effective spreads, and Abdi-Ranaldo effective spreads. Spreads increase with the SAD Composite variable in all cases except the AR spreads. The increases are consistently smallest for the largest-firm tercile; tercile 2 increases are a bit larger than tercile 3 increases though their magnitudes are similar and not likely significantly different from each other. Again, only the AR spreads case presents us with statistically insignificant SAD effects. All other cases display strong statistical significance, with *t*-tests in excess of 2.5.

[Table 7]

Overall, the tercile results suggest the impatience and risk aversion associated with SAD have greater economic impact on the spreads of smaller firms relative to larger firms.

3.4 International liquidity metrics

To provide further evidence identifying the effect of SAD on spreads, we turn our attention to the analysis of data from markets located in countries other than the United States. SAD varies in intensity and prevalence based on latitude, and therefore by considering spreads data from markets around the world at different latitudes, we can test the identification of spread seasonality arising due to seasonal light exposure.

We consider a collection of large, broad-based markets that provide representation across different latitude groupings that span the globe. The group furthest to the north is the northern temperate zone, located at latitudes above 40 degrees north. Exchanges in Norway, Germany, the United Kingdom, France, Canada, and Italy are located in this zone. The northern sub-tropics region spans 23.5 degrees north to 40 degrees north, and markets in China, Japan, and Hong Kong are located in this region. The tropical zone is between 23.5 degrees north and 23.5 degrees south, and includes Brazil, Thailand, the Philippines, and Indonesia. Finally, the southern sub-tropics and temperate zone countries, at latitudes 23.5 degrees south and higher, are New Zealand, Argentina, Australia, Chile, and South Africa.

For each country in our sample, we collect stock-level data from Datastream for all available firms, yielding millions of firm-day observations for each latitude grouping: 9 million for the most northern group, over 15 million for the northern subtropics, and about 3 million for the tropics region and the southern sub-tropics/temperate zone. Summary statistics appear in Table 8; more granular summary statistics, on a country-by-country basis, are tabulated in an online appendix (Table A1). Starting with the stock characteristics in Table 8, we see the average firm market capitalization, converted to U.S. dollars, is over $1.5 billion for the northern temperate zone and northern subtropic groupings, and is a bit below $1 billion for the tropics and southern sub-tropics/temperate zone regions. The average share price is highest for the most northern latitude group at $13.90 and drops monotonically through the groups to a low of $2.47 for the most southern latitude group. The tropics region exhibits the highest average volume of daily shares traded (over 9 million), and also the most volatile volume of shares traded; in contrast the northern temperate zone has the lowest share volume (683,000) and share volume volatility. The return volatility distributions are fairly similar to each other across the latitude zones.

[Table 8]

Regarding the low-frequency liquidity metrics, the mean EOD spreads are largest for the most southern group, at 808 bps. The mean CS and AR effective spreads are also largest for that region, at 547 and 645 bps respectively. All three liquidity measures tend to be smaller for the northern temperate region, and are smaller still for the northern subtropics and topics, with mean values between 89 and 304 bps in those regions. Referring back to the bottom portion of Table 1, we see the U.S. low-frequency spreads are comparatively much smaller and less volatile than for all of the international regions represented in Table 8.

Turning to formal analysis of the spreads, we estimate Equation 1 for each of the four regions. Results appear in Table 9. Panels A, B, C, and D correspond to the northern temperate region, the northern sub-tropics, the tropics, and the southern sub-tropics/temperate zones respectively. That is, results appear from furthest north to furthest south. The key regressor in each case is the SAD Composite variable because we hypothesize the EOD quoted spread and CS and AR effective spreads include the effects of both seasonally varying risk aversion and seasonally varying impatience. For the southern region, we shift the SAD Composite variable by six months to adjust for the fact that the timing of daylight exposure in the southern hemisphere is offset by six months relative to the northern hemisphere. In the interest of brevity, we present results for the Full models only; results based on the Base models are qualitatively similar.

In Panel A, which covers the northern temperate region, we see all three of the low-frequency spreads measures vary with SAD. The end-of-day spreads increase by 1.602 bps, CS spreads by 1.853 bps, and AR spreads by 3.200 bps, each statistically significantly. These effects are less strong in the northern sub-tropic region, Panel B, with only the EOD spreads increasing significantly at 0.950 bps. This is not unexpected in light of the fact that medical research finds the effects of SAD are most noticeable at latitudes above 40 degrees. In Panel C, the tropics exhibit the weakest SAD effect, as expected for an equatorial region where light exposure is fairly constant through the year. Most of the spreads measures exhibit no significant seasonality. The southern regions in Panel D, a blend of sub-tropical and temperate countries, exhibit significantly increased spreads with SAD in all cases. The relatively bigger SAD Composite coefficient estimates in Panel D versus Panel A are largely driven by the fact that unconditional spreads are larger in the southern region than in the northern temperate region. Overall, the international results are consistent with those observed based on U.S. data.

[Table 9]

4. Conclusion

We live in a world increasingly influenced by technology. In financial markets, computers execute trades at speeds that exceed humans' ability to process information. We test whether human behavior plays any role in the generation and consumption of liquidity. We initially consider spreads based on 10 years of intraday data for some of the largest U.S. stocks and find that seasonally varying risk aversion and seasonally varying impatience among informed traders, market makers, and other market participants play a statistically significant and economically large role, even after controlling for known determinants of spreads. In cross-sectional analysis, we find the seasonal effects are largest for small firms. To aid identification, we also consider data for an array of countries other than the U.S., exploiting the notion that seasonal variation in light exposure – and hence risk aversion and impatience – is strongest for high-latitude countries. Further, effects are offset by six months for southern hemisphere countries. On balance, we find human nature influences liquidity through seasonally varying daylight. Our findings suggest algorithmic trading, while pervasive, does not eliminate all traces of human nature from liquidity provision and consumption, and indeed human nature remains an economically large component of spreads even in the modern machine era.

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Table 1
Summary Statistics

The table reports summary statistics for the sample period staring in January 2010 through December 2019. The data are from CRSP and TAQ databases. The top portion of the table contains summary statistics for stock characteristics such as market capitalization, share price, daily trading volume, and volatility computed as the the difference between the high and low prices of the day scaled by their average and multiplied by 100. The middle portion of the table reports on high-frequency liquidity metrics obtained from TAQ, including quoted, effective, and realized spreads as well as price impacts. We compute price impacts and realized spreads for two horizons, 60 and 300 seconds after the trade. The bottom portion of the table reports on three low-frequency liquidity metrics, including the end-of-day (EOD) quoted spread computed using CRSP quotes as well as two effective spread estimators proposed by Corwin and Schultz (2012) and Abdi and Ranaldo (2017), respectively, CS and AR. When aggregating, we first compute the averages of all variables for each stock and then compute sample characteristics across stocks. The full sample contains over 2.1 million stock-day observations. For some variables, fewer than the full sample number of observations are available, most notably CS and AR which discard negative estimates.

	Mean	St. dev.	Median	25th	75th
Stock characteristics:					
Market capitalization, $ millions	14,263	28,605	5,259	2,682	13,269
Price, $	51.02	41.43	42.27	27.56	61.44
Volume, thousands of shares	2,497.23	4,892.66	1,220.62	583.52	2,682.20
Natural log volume	13.73	1.38	13.77	12.99	14.59
Volatility	0.02	0.01	0.02	0.02	0.03
High-frequency liquidity metrics, bps:					
Quoted spread	7.42	16.41	5.31	3.61	7.85
Effective spread	5.77	11.21	4.30	2.91	6.08
Price impact, 60s	4.24	2.53	3.75	2.65	4.99
Price impact, 300s	4.58	3.29	3.94	2.66	5.34
Realized spread, 60s	1.51	9.69	0.42	0.16	1.05
Realized spread, 300s	1.17	9.05	0.32	0.16	0.69
Low-frequency liquidity metrics, bps:					
EOD quoted spread	6.14	18.88	3.44	2.46	5.62
CS effective spread	96.83	34.78	88.17	72.57	111.39
AR effective spread	128.52	42.57	121.18	98.84	146.92

Table 2
SAD, Displayed Liquidity, and Trading Costs

The table examines the relationship between the SAD Composite variable and quoted spreads (Panel A) and the SAD Composite variable and effective spreads (Panel B). The sample period spans January 2010 through December 2019. The reported coefficients are obtained from the regression of the following form, where SAD is a place-holder for the SAD Composite variable:

$$DepVar_{it} = \alpha_i + \gamma_{year} + \beta_1 SAD_t + \beta_2 Volume_{it} + \beta_3 Volatility_{it} + \varepsilon_{it}.$$

DepVar is the effective or quoted spread in stock i on day t, *SAD* is a place-holder for the SAD Composite variable (i.e., the sum of SAD *Incidence* and SAD *Onset/Recovery*), *Volume* is the lagged natural logarithm of daily number of shares traded, and *Volatility* is lagged difference between the highest and lowest price of the day scaled by the average of the two prices. In specifications [1] and [3], we report the results from the Base models that do not include the control variables. In specifications [2] and [4], we report the results from the Full models with control variables. The models are estimated using ordinary least squares, controlling for stock and year fixed effects, and the standard errors are clustered by firm and date. *** indicate statistical significance at the 1% level. The sample contains over 2.1 million stock-day observations.

	Quoted spread		Effective spread	
	Base	Full	Base	Full
	[1]	[2]	[3]	[4]
SAD Composite	0.399***	0.327***	0.243***	0.185***
	(0.05)	(0.04)	(0.03)	(0.03)
Volatility		0.659***		0.515***
		(0.11)		(0.08)
Volume		-1.322***		-0.916***
		(0.34)		(0.24)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Adj. R^2	0.66	0.68	0.65	0.67

Table 3
SAD and Trading Cost Components

The table examines the relation between SAD Onset/Recovery and price impacts (Panel A) and between SAD Incidence and realized spreads (Panel B). The sample period spans January 2010 through December 2019. We compute price impacts and realized spreads for two horizons, 60 and 300 seconds after the trade. The reported coefficients are obtained from the regression of the following form, where *SAD* is a place-holder for $Onset/Recovery$ or *Incidence*:

$$DepVar_{it} = \alpha_i + \gamma_{year} + \beta_1 SAD_t + \beta_2 Volume_{it} + \beta_3 Volatility_{it} + \varepsilon_{it},$$

where *DepVar* is the price impact or realized spread in stock i on day t, *SAD* is SAD Onset/Recovery when the dependent variable is the price impact and SAD Incidence when the dependent variable is the realized spread, *Volume* is the lagged natural logarithm of daily number of shares traded, and *Volatility* is the lagged difference between the highest and lowest price of the day scaled by the average of the two prices. In specifications [1] and [3], we report the results from the Base models that do not include the control variables. In specifications [2] and [4], we report the results from the Full models with control variables. The models are estimated using ordinary least squares, controlling for stock and year fixed effects, and the standard errors are clustered by firm and date *** and ** indicate statistical significance at the 1% and 5% levels. The sample contains over 2.1 million stock-day observations.

Panel A: Price impacts				
	60 seconds		300 seconds	
	Base	Full	Base	Full
	[1]	[2]	[3]	[4]
SAD Onset/Recovery	0.325***	0.241***	0.363***	0.258***
	(0.05)	(0.04)	(0.05)	(0.05)
Volatility		0.415***		0.451***
		(0.05)		(0.06)
Volume		-0.070		-0.291***
		(0.07)		(0.09)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Adj. R^2	0.51	0.54	0.47	0.49

Panel B: Realized spreads				
SAD Incidence	0.118***	0.130***	0.116***	0.127***
	(0.03)	(0.03)	(0.03)	(0.03)
Volatility		0.112***		0.076**
		(0.04)		(0.03)
Volume		-0.828***		-0.610***
		(0.20)		(0.17)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Adj. R^2	0.61	0.62	0.55	0.55

Table 4
SAD and Low-Frequency Liquidity Metrics

The table examines the relation between the SAD composite variable and each of three low-frequency liquidity proxies: the end of day spread (EOD), which proxies for displayed liquidity, the Corwin-Schultz (CS) metric – a proxy for trading costs, and the Abdi-Ranaldo (AR) metric – also a proxy for trading costs. The sample period spans January 2010 through December 2019. The reported coefficients are obtained from the regression of the following form:

$$DepVar_{it} = \alpha_i + \gamma_{year} + \beta_1 SAD_t + \beta_2 Volume_{it} + \beta_3 Volatility_{it} + \varepsilon_{it},$$

where *DepVar* is one of the three above-mentioned low-frequency metrics in stock i on day t, *SAD* is a place-holder for the SAD composite variable (i.e., the sum of *Incidence* and *Onset*/*Recovery*), *Volume* is the lagged natural logarithm of daily number of shares traded, and *Volatility* is the lagged difference between the highest and lowest price of the day scaled by the average of the two prices. For each dependent variable, we report the results from the Base regression model that does not include the control variables and from the Full model that includes the control variables. The models are estimated using ordinary least squares, controlling for stock and year fixed effects, and the standard errors are clustered by firm and date. *** indicates statistical significance at the 1% level. The EOD sample contains over 2.1 million stock-day observations, and the CS and AR samples contain about 1.3 million and 0.7 million observations respectively because both the CS and AR methods discard negative estimates.

	EOD		CS		AR	
	Base	Full	Base	Full	Base	Full
SAD Composite	0.245***	0.177***	5.297***	3.065***	3.707	2.445
	(0.06)	(0.05)	(1.20)	(0.72)	(2.66)	(2.29)
Volume		-0.798***		4.485***		9.739***
		(0.27)		(0.95)		(2.51)
Volatility		0.488***		22.97***		19.25***
		(0.09)		(1.10)		(2.23)
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Adj. R^2	0.42	0.44	0.18	0.35	0.15	0.22

Table 5
Cross-Sectional Summary Statistics

The table reports summary statistics for the data sorted daily into size terciles over the sample period January 2010 through December 2019. The data are from CRSP and TAQ databases. Panel A corresponds to the largest firms (tercile 1), Panel B corresponds to smaller firms (tercile 2), and Panel C corresponds to the smallest firms (tercile 3). Summary statistics appear for the following stock characteristics: market capitalization, share price, daily trading volume, and volatility computed as the the difference between the high and low prices of the day scaled by their average and multiplied by 100. Summary statistics also appear for the following low-frequency liquidity metrics: the end-of-day (EOD) quoted spread, the Corwin and Schultz (2012) (CS) effective spread, and the Abdi and Ranaldo (2017) (AR) effective spread. When aggregating, we first compute the averages of all variables for each stock and then compute sample characteristics across stocks. Each tercile contains over over 700,000 stock-day observations. For some variables, fewer than the full sample number of observations are available, most notably CS and AR which discard negative estimates.

Panel A: Tercile 1

	Mean	St. dev.	Median	25th	75th
Stock characteristics:					
Market capitalization, $ millions	27,129	36,099	16,329	10,617	26,488
Price, $	70.22	49.92	58.54	39.92	83.01
Volume, thousands of shares	4,085.76	7,386.85	2, 248.97	1,344.80	4,215.09
Volatility	0.02	0.01	0.02	0.02	0.03
High-frequency liquidity metrics, bps:					
Quoted spread	4.12	3.32	3.35	2.76	4.60
Effective spread	3.30	2.57	2.73	2.23	3.57
Price impact, 60s	2.93	1.67	2.53	2.06	3.37
Price impact, 300s	2.96	1.78	2.49	2.04	3.36
Realized spread, 60s	0.37	1.56	0.17	0.07	0.42
Realized spread, 300s	0.34	1.36	0.21	0.10	0.43
Low-frequency liquidity metrics, bps:					
EOD quoted spread	3.96	12.79	2.25	1.82	3.31
CS effective spread	84.82	25.27	80.36	67.60	98.57
AR effective spread	112.49	48.48	106.87	86.95	126.99

Panel B: Tercile 2

Stock characteristics:					
Market capitalization, $ millions	5,904	3,171	5,325	3,974	7,103
Price, $	51.11	42.42	42.74	27.44	61.40
Volume, thousands of shares	2,432.09	4,104.17	1,123.55	626.12	2,312.91
Volatility	0.03	0.01	0.02	0.02	0.03
High-frequency liquidity metrics, bps:					
Quoted spread	6.18	4.19	5.04	4.00	6.87
Effective spread	4.93	3.29	4.13	3.26	5.59
Price impact, 60s	4.10	1.79	3.70	3.00	4.70
Price impact, 300s	4.35	2.22	3.89	3.04	5.01
Realized spread, 60s	0.83	2.02	0.38	0.13	0.89
Realized spread, 300s	0.58	1.48	0.28	0.07	0.63
Low-frequency liquidity metrics, bps:					
EOD quoted spread	5.19	13.77	3.28	2.58	4.98
CS effective spread	99.01	38.07	90.72	73.04	117.75
AR effective spread	129.64	50.38	121.83	95.73	153.69

(Table 5 continues on the next page)

(Table 5 continued)

Panel C: Tercile 3					
	Mean	St. dev.	Median	25th	75th
Stock characteristics:					
Market capitalization, $ millions	2,388	1,685	2,158	1,644	2,757
Price, $	33.45	35.75	27.10	15.84	41.13
Volume, thousands of shares	1,932.30	4356.67	741.57	356.60	1,679.82
Volatility	0.03	0.02	0.03	0.02	0.04
High-frequency liquidity metrics, bps:					
Quoted spread	10.72	20.45	7.71	5.79	11.32
Effective spread	8.29	13.86	6.02	4.70	8.95
Price impact, 60s	5.81	2.92	5.01	4.02	6.88
Price impact, 300s	6.44	3.76	5.51	4.25	7.55
Realized spread, 60s	2.48	12.28	0.88	0.38	2.01
Realized spread, 300s	1.86	11.56	0.57	0.20	1.35
Low-frequency liquidity metrics, bps:					
EOD quoted spread	8.48	19.98	5.26	3.81	9.07
CS effective spread	114.95	45.21	104.36	82.86	139.62
AR effective spread	153.83	54.47	140.94	114.45	182.64

Table 6
Cross-Sectional Results: SAD and Trading Cost Components

The table examines the relationship between the SAD variables and various spreads and trading cost metrics for each of three size terciles over the sample period January 2010 through December 2019. Panel A corresponds to the largest firms (tercile 1), Panel B corresponds to smaller firms (tercile 2), and Panel C corresponds to the smallest firms (tercile 3). The reported coefficients are obtained from the regression of the following form, where SAD is a place-holder for the appropriate SAD variable:

$$DepVar_{it} = \alpha_i + \gamma_{year} + \beta_1 SAD_t + \beta_2 Volume_{it} + \beta_3 Volatility_{it} + \varepsilon_{it}.$$

DepVar is the effective or quoted spread in stock *i* on day *t*; *SAD* is a place-holder for the SAD Composite variable, the SAD *Incidence*, or SAD *Onset/Recovery* variable as appropriate; *Volume* is the lagged natural logarithm of daily number of shares traded; and *Volatility* is lagged difference between the highest and lowest price of the day scaled by the average of the two prices. The models are estimated using ordinary least squares, controlling for stock and year fixed effects, and the standard errors are clustered by firm and date. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels respectively. Each tercile contains over 700,000 stock-day observations. For some variables, fewer than the full sample number of observations are available.

Panel A: Tercile 1				
	Price impact, 60s	Price impact, 300s	Realized spread, 60s	Realized spread, 300s
	[1]	[2]	[3]	[4]
SAD Onset/Recovery	0.115***	0.128***		
	(0.029)	(0.031)		
SAD Incidence			0.042***	0.048***
			(0.010)	(0.011)
Volatility	21.854***	21.580***	2.981	3.272
	(4.146)	(4.184)	(4.293)	(3.719)
Volume	0.061	-0.007	-0.321	-0.255
	(0.058)	(0.074)	(0.233)	(0.210)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Adj. R^2	0.591	0.481	0.407	0.277

(Table 6 continues on the next page)

(Table 6 continued)

Panel B: Tercile 2				
	Price impact, 60s	Price impact, 300s	Realized spread, 60s	Realized spread, 300s
	[1]	[2]	[3]	[4]
SAD Onset/Recovery	0.246***	0.261***		
	(0.047)	(0.050)		
SAD Incidence			0.120***	0.112***
			(0.018)	(0.018)
Volatility	28.483***	28.781***	0.040	-0.800
	(4.973)	(5.585)	(0.693)	(0.629)
Volume	0.049	-0.091	-0.353***	-0.209***
	(0.057)	(0.067)	(0.037)	(0.029)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Adj. R^2	0.561	0.514	0.632	0.336

Panel C: Tercile 3				
	Price impact, 60s	Price impact, 300s	Realized spread, 60s	Realized spread, 300s
	[1]	[2]	[3]	[4]
SAD Onset/Recovery	0.347***	0.369***		
	(0.064)	(0.071)		
SAD Incidence			0.223***	0.217***
			(0.070)	(0.068)
Volatility	49.740**	57.271***	23.310***	15.845***
	(4.825)	(5.982)	(6.835)	(5.806)
Volume	-0.209	-0.614***	-1.643***	-1.247***
	(0.128)	(0.177)	(0.363)	(0.330)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Adj. R^2	0.437	0.387	0.639	0.576

Table 7
Cross-Sectional Results: SAD, Displayed Liquidity and Trading Costs

The table examines the relationship between the SAD variables and various quoted and effective spreads for each of three size terciles over the sample period January 2010 through December 2019. Panel A corresponds to the largest firms (tercile 1), Panel B corresponds to smaller firms (tercile 2), and Panel C corresponds to the smallest firms (tercile 3). The reported coefficients are obtained from the regression of the following form, where SAD is a place-holder for the SAD Composite variable:

$$DepVar_{it} = \alpha_i + \gamma_{year} + \beta_1 SAD_t + \beta_2 Volume_{it} + \beta_3 Volatility_{it} + \varepsilon_{it}.$$

DepVar is the effective or quoted spread in stock i on day t, *SAD* is a place-holder for the SAD Composite variable, *Volume* is the lagged natural logarithm of daily number of shares traded, and *Volatility* is lagged difference between the highest and lowest price of the day scaled by the average of the two prices. The models are estimated using ordinary least squares, controlling for stock and year fixed effects, and the standard errors are clustered by firm and date. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels respectively. Each tercile contains over 700,000 stock-day observations. For some variables, fewer than the full sample number of observations are available, most notably CS and AR which discard negative estimates.

Panel A: Tercile 1					
	Quoted [1]	Effective [2]	EOD [3]	CS [4]	AR [5]
SAD Composite	0.125***	0.064***	0.089**	2.384**	2.232
	(0.025)	(0.019)	(0.038)	(0.700)	(2.129)
Volatility	29.693***	23.966***	17.616**	2,314.475***	1,936.113***
	(8.064)	(6.525)	(7.027)	(142.194)	(296.481)
Volume	-0.412	-0.257	-0.090	5.607***	11.859***
	(0.323)	(0.267)	(0.266)	(1.243)	(3.024)
Firm FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Adj. R^2	0.577	0.584	0.469	0.307	0.196

(Table 7 continues on the next page)

(Table 7 continued)

Panel B: Tercile 2					
	Quoted [1]	Effective [2]	EOD [3]	CS [4]	AR [5]
SAD Composite	0.534***	0.300***	0.299**	3.835**	2.989
	(0.102)	(0.066)	(0.121)	(0.841)	(2.791)
Volatility	95.399***	71.547***	61.101***	2,235.467***	1,867.467***
	(14.472)	(10.193)	(10.746)	(86.639)	(124.825)
Volume	-2.744***	-1.889***	-1.716***	4.527***	10.750***
	(0.662)	(0.459)	(0.537)	(0.837)	(1.925)
Firm FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Adj. R^2	0.677	0.658	0.485	0.364	0.225

Panel C: Tercile 3					
	Quoted [1]	Effective [2]	EOD [3]	CS [4]	AR [5]
SAD Composite	0.327***	0.185***	0.177***	3.065***	2.445
	(0.043)	(0.030)	(0.049)	(0.720)	(2.289)
Volatility	65.892***	51.475***	48.840***	2,296.780***	1,925.248***
	(11.367)	(8.093)	(9.459)	(109.639)	(223.001)
Volume	-1.322***	-0.916***	-0.798***	4.485***	9.739***
	(0.336)	(0.241)	(0.265)	(0.945)	(2.511)
Firm FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Adj. R^2	0.677	0.668	0.443	0.350	0.223

Table 8
International Summary Statistics

The table reports summary statistics for each of the latitude groupings over the sample period January 2010 through December 2019. The data are from Datastream. Summary statistics for each latitude grouping appear for the following stock characteristics: market capitalization, share price, daily trading volume, and volatility computed as the the difference between the high and low prices of the day scaled by their average and multiplied by 100. Summary statistics for each latitude grouping also appear for the following low-frequency liquidity metrics: the end-of-day (EOD) quoted spread, the Corwin and Schultz (2012) (CS) effective spread, and the Abdi and Ranaldo (2017) (AR) effective spread. When aggregating, we first compute the averages of all variables for each stock and then compute sample characteristics across stocks. Panel A corresponds to the Northern Temperate Zone countries: Norway, Germany, the United Kingdom, France, Canada, and Italy. Panel B corresponds to the Northern Sub-Tropics countries: China, Japan, and Hong Kong. Panel C corresponds to the Tropics countries: Brazil, Thailand, the Philippines, and Indonesia. Panel D corresponds to the Southern Sub-Tropics and Temperate Zone countries: New Zealand, Argentina, Australia, Chile, and South Africa. The number of stock-day observations in each full sample is as follows: 9,059,434 for Panel A, 15,699,170 for Panel B, 3,066,550 for Panel C, and 3,148,766 for Panel D. For some variables, fewer than the full sample number of observations are available, most notably CS and AR which discard negative estimates.

Panel A: Northern Temperate Zone (Above 40° N)					
	Mean	St. dev.	Median	25th	75th
Stock characteristics					
Market capitalization, $ millions	1,768	8,107	107	28	493
Price, $	13.90	31.05	4.06	0.99	13.10
Volume, thousands of shares	683.00	4734.10	46.83	6.83	258.61
Volatility	0.05	0.06	0.04	0.02	0.06
Low-frequency liquidity metrics, bps					
EOD quoted spread	532.66	948.71	259.12	100.83	560.92
CS effective spread	282.84	504.19	150.01	101.26	262.33
AR effective spread	394.36	596.38	227.88	150.28	389.48

Panel B: Northern Subtropics (23.5° N to 40° N)					
Stock characteristics					
Market capitalization, $ millions	1,631	6,887	0.495	0.140	1.099
Price, $	8.33	22.78	2.76	0.96	7.76
Volume, thousands of shares	7,028.53	15,371.57	2,648.88	208.287	8,068.13
Volatility	0.04	0.02	0.04	0.03	0.05
Low-frequency liquidity metrics, bps					
EOD quoted spread	88.74	137.80	33.44	12.88	107.81
CS effective spread	153.87	91.24	142.15	109.43	173.41
AR effective spread	210.33	117.46	185.35	153.34	231.39

(Table 8 continues on the next page)

(Table 8 continued)

Panel C: Tropics (Between 23.5° N and 23.5° S)					
	Mean	St. dev.	Median	25th	75th
Stock characteristics					
Market capitalization, $ millions	961	3,640	120	36	538
Price, $	4.61	23.24	0.20	0.05	1.40
Volume, thousands of shares	9,704.36	40,369.49	1,500.58	133.82	6,110.67
Volatility	0.04	0.03	0.03	0.03	0.05
Low-frequency liquidity metrics, bps					
EOD quoted spread	247.21	365.60	118.82	78.21	258.40
CS effective spread	214.34	184.60	171.65	122.35	257.59
AR effective spread	303.65	227.73	236.96	171.20	367.81

Panel D: Southern Sub-Tropics and Temperate Zone (23.5° S and Higher)					
Stock characteristics					
Market capitalization, $ millions	752	3,929	57	17	277
Price, $	2.47	9.27	0.32	0.10	1.39
Volume, thousands of shares	1,367.54	7,511.59	286.30	97.03	884.49
Volatility	0.07	0.07	0.05	0.03	0.08
Low-frequency liquidity metrics, bps					
EOD quoted spread	807.96	1,297.42	498.61	219.90	951.29
CS effective spread	546.54	826.21	300.83	142.48	575.38
AR effective spread	645.12	838.17	431.16	199.00	736.36

Table 9
SAD and International Low-Frequency Liquidity Metrics

The table examines, from an international perspective, the relation between the SAD composite variable and each of three low-frequency liquidity proxies: the end of day spread (EOD), which proxies for displayed liquidity, the Corwin-Schultz (CS) metric – a proxy for trading costs, and the Abdi-Ranaldo (AR) metric – also a proxy for trading costs. Results appear for each latitude grouping: the northern temperate zone in Panel A (Norway, Germany, the United Kingdom, France, Canada, and Italy), the northern sub-tropics in Panel B (China, Japan, and Hong Kong), the tropics in Panel C (Brazil, Thailand, the Philippines, and Indonesia), and the southern sub-tropics and temperate zone in Panel D (New Zealand, Argentina, Australia, Chile, and South Africa). The sample period spans January 2010 through December 2019. The reported coefficients are obtained from the regression of the following form:

$$DepVar_{it} = \alpha_i + \gamma_{year} + \beta_1 SAD_t + \beta_2 Volume_{it} + \beta_3 Volatility_{it} + \varepsilon_{it},$$

where *DepVar* is one of the three above-mentioned low-frequency metrics in stock i on day t, *SAD* is a place-holder for the SAD composite variable (i.e., the sum of *Incidence* and *Onset/Recovery*), *Volume* is the lagged natural logarithm of daily number of shares traded, and *Volatility* is the lagged difference between the highest and lowest price of the day scaled by the average of the two prices. The models are estimated using ordinary least squares, controlling for stock and year fixed effects, and the standard errors are clustered by firm and date. *** and ** indicate statistical significance at the 1% and 5% levels.

Panel A: Northern Temperate Zone (Above 40° N)			
	EOD [1]	CS [2]	AR [3]
SAD Composite	1.602**	1.853***	3.200***
	(0.79)	(0.44)	(0.88)
Volume	-57.554***	-18.075***	-29.204***
	(1.45)	(1.09)	(1.08)
Volatility	35.396***	34.987***	36.105***
	(1.01)	(0.93)	(0.96)
Firm FE	Y	Y	Y
Year FE	Y	Y	Y
N (millions)	8.8	6.2	5.4
Adj. R^2	0.64	0.60	0.57

Panel B: North Sub-Tropics (23.5° N to 40° N)			
SAD Composite	0.950***	-0.679	-1.073
	(0.33)	(0.54)	(1.37)
Volume	-26.429***	-0.312	-6.450***
	(1.91)	(2.23)	(2.49)
Volatility	8.508***	22.420***	21.878***
	(1.36)	(1.71)	(1.93)
Firm FE	Y	Y	Y
Year FE	Y	Y	Y
N (millions)	15.2	9.7	8.4
Adj. R^2	0.55	0.44	0.33

(Table 9 continues on the next page)

(Table 9 continued)

Panel C: Tropics (Between 23.5° N and 23.5° S)			
	EOD [1]	CS [2]	AR [3]
SAD Composite	-0.316	-0.998*	0.687
	(0.86)	(0.51)	(0.95)
Volume	-40.208***	-12.917***	-23.210***
	(2.96)	(1.86)	(2.04)
Volatility	25.410***	33.996***	32.955***
	(2.78)	(3.14)	(4.10)
Firm FE	Y	Y	Y
Year FE	Y	Y	Y
N (millions)	3.0	1.2	1.1
Adj. R^2	0.51	0.54	0.45

Panel D: Southern Sub-Tropics & Temperate Zone (23.5° S and Higher)			
SAD Composite	5.408***	1.601**	2.306**
	(1.49)	(0.82)	(1.11)
Volume	-70.480***	-37.316***	-37.644***
	(1.87)	(1.53)	(1.50)
Volatility	49.384***	51.800***	51.800***
	(1.38)	(1.28)	(1.24)
Firm FE	Y	Y	Y
Year FE	Y	Y	Y
N (millions)	3.0	2.2	2.0
Adj. R^2	0.58	0.74	0.67

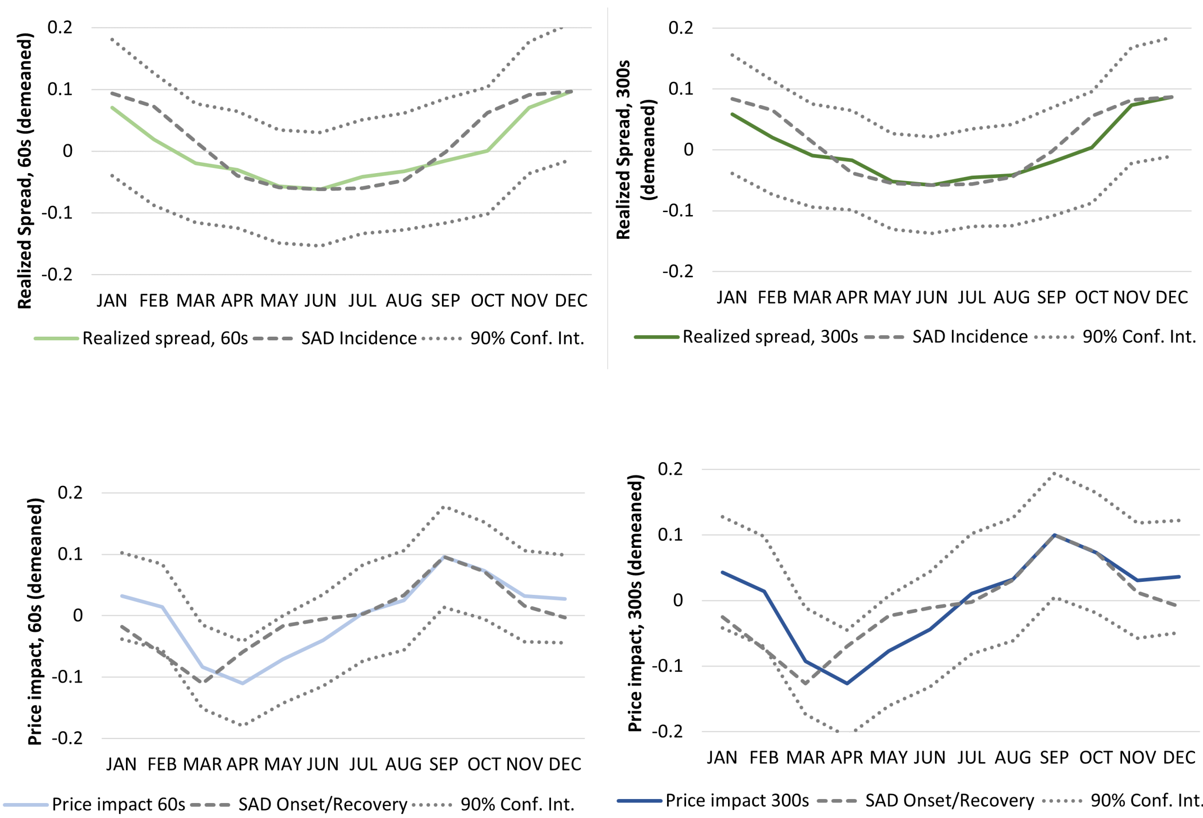

Figure 1
SAD and liquidity costs: realized spreads and price impact

The figure plots monthly estimates of realized spread, 60s (light green solid line in the top/left chart); and realized spread, 300s (dark green solid line in the top/right chart); price impact, 60s (light blue solid line in the bottom/left chart); price impact, 300s (dark blue solid line in the bottom/right chart); and SAD Incidence (long-dashed line) for the sample period January 2010 through December 2019. The spread measures are three-month centered moving averages. SAD Incidence is the fitted value implied by the SAD Incidence coefficient from estimating Equation 1. All series have been demeaned for ease of comparison across plots. Dotted lines represent a 90% confidence interval around the metric.

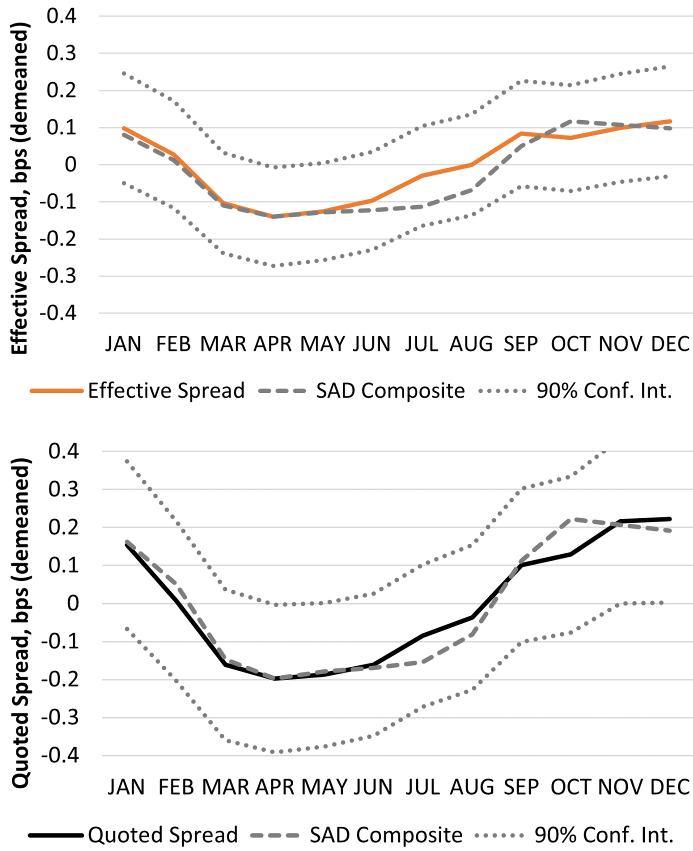

Figure 2
SAD and liquidity costs: effective and quoted spreads

The figure plots monthly estimates of effective spreads (orange solid line in the top chart) quoted spreads (black solid line in the bottom chart), and SAD Composite (long-dashed line) for the sample period January 2010 through December 2019. The quoted spread is computed from intraday TAQ data as the difference between the best prevailing national offer quote and the best prevailing national bid quote scaled by the corresponding midpoint. The spread measures are three-month centered moving averages. SAD Composite is the fitted value implied by the SAD Composite coefficient from estimating Equation 1. All series have been demeaned for ease of comparison across plots. Dotted lines represent a 90% confidence interval around the spread.

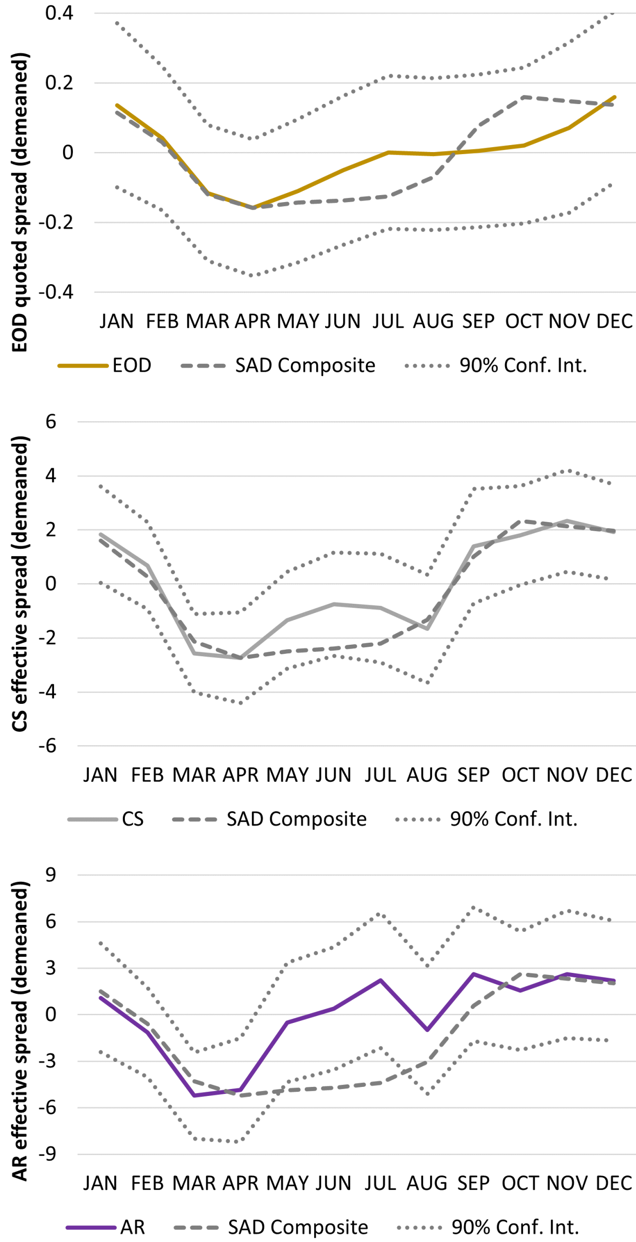

Figure 3
SAD and low-frequency liquidity metrics

The figure plots monthly estimates of end-of-day (EOD; solid yellow line in the top chart) quoted spreads, Corwin-Schultz (CS; solid grey line in the middle chart) effective spread estimate, Abdi-Ranaldo (AR; solid purple line in the bottom chart) effective spread estimate, and SAD Composite (long-dashed line) for the sample period staring in January 2010 through December 2019. The spread measures are three-month centered moving averages. SAD Composite is the fitted value implied by the SAD Composite coefficient from estimating Equation 1. All series have been demeaned for ease of comparison across plots. Dotted lines represent a 90% confidence interval around the spread.

Table A1
Country-by Country Summary Statistics
(Calculated on Means of Variables Firm-by-Firm)

	Mean	Std	Min	Max	Skew	Kurt
Argentina:						
Market capitalization, $ millions	675.62	1419.3	3.28	11023	5.216	34.47
Local Currency Price	74.655	317.93	0.95	2904.6	8.613	77.18
Price, $	3.120	6.60	0.17	48.51	5.096	29.77
Return %	0.289	0.30	-0.25	1.94	3.311	14.46
Volume (millions of shares)	0.231	0.66	0.00	5.00	5.588	35.97
Natural log volume	3.264	1.77	-0.72	8.10	0.389	0.27
Volatility	0.039	0.01	0.02	0.08	1.160	3.95
EOD quoted spread	227.62	183.43	40.12	1347.0	3.266	16.46
CS effective spread	172.18	42.61	88.03	338.24	1.544	3.34
AR effective spread	240.42	48.05	136.76	447.33	1.501	4.18
Australia:						
Market capitalization, $ millions	626.02	4139.8	0.08	96829	16.003	306.17
Local Currency Price	2.784	12.35	0.00	187.40	7.807	67.31
Price, $	2.241	9.75	0.00	173.65	8.220	81.79
Return %	0.331	2.12	-20.05	66.19	16.271	438.18
Volume (millions of shares)	1.131	3.17	0.00	84.90	12.820	264.34
Natural log volume	5.082	1.66	-1.28	10.51	-0.191	0.65
Volatility	0.073	0.07	0.00	0.67	4.589	28.95
EOD quoted spread	880.94	1343.0	10.56	20000	7.920	92.39
CS effective spread	610.93	862.47	8.27	6666.7	4.167	21.56
AR effective spread	719.29	871.71	11.97	6931.5	4.139	21.88
Brazil:						
Market capitalization, $ millions	2051.5	6546.7	0.00	74516	7.097	60.27
Local Currency Price	62.691	166.93	0.11	1509.3	5.535	34.79
Price, $	19.380	47.09	0.03	408.72	5.139	29.34
Return %	0.305	1.18	-5.42	17.63	7.624	102.42
Volume (millions of shares)	1.940	19.46	0.00	424.56	20.646	446.14
Natural log volume	3.147	2.96	-2.10	11.43	0.384	-0.92
Volatility	0.040	0.04	0.00	0.32	4.135	24.54
EOD quoted spread	384.97	632.66	14.63	4996.9	3.060	11.38
CS effective spread	184.56	241.21	2.28	3155.5	7.418	79.24
AR effective spread	270.79	275.60	2.50	3228.6	5.466	47.17
Canada:						
Market capitalization, $ millions	1341.5	5367.5	0.00	92961	9.372	116.06
Local Currency Price	12.329	26.20	0.02	482.57	10.172	151.58
Price, $	10.887	23.56	0.02	431.06	11.113	176.75
Return %	0.108	0.87	-22.50	14.25	-6.989	338.16
Volume (millions of shares)	0.278	0.57	0.00	7.14	4.377	27.13
Natural log volume	3.563	1.92	-2.07	8.62	0.095	-0.72
Volatility	0.042	0.04	0.00	0.66	5.352	59.50
EOD quoted spread	346.79	497.29	10.69	7014.5	5.235	41.60
CS effective spread	236.15	347.92	10.34	6534.4	7.314	90.35
AR effective spread	323.24	389.70	16.42	6791.1	6.176	67.67

(Table A1 continues on the next page)

(Table A1 continued)

	Mean	Std	Min	Max	Skew	Kurt
Chile:						
Market capitalization, $ millions	1673.5	3041.7	0.00	20219	3.519	14.49
Local Currency Price	2237.8	5093.7	0.87	38084	4.650	25.72
Price, $	3.991	9.10	0.00	66.94	4.640	25.40
Return %	0.410	1.46	-4.52	7.41	2.564	11.88
Volume (millions of shares)	6.039	25.82	0.00	296.26	9.234	99.69
Natural log volume	5.151	2.44	0.36	12.13	0.269	-0.30
Volatility	0.026	0.02	0.00	0.16	3.834	17.25
EOD quoted spread	385.27	357.35	46.46	1934.2	1.949	3.99
CS effective spread	123.23	74.14	25.74	426.57	1.808	3.54
AR effective spread	163.94	97.32	31.50	833.82	3.138	15.51

China:						
Market capitalization, $ millions	1888.7	6691.2	0.00	221832	20.024	533.67
Local Currency Price	19.816	18.12	0.38	353.32	5.612	67.55
Price, $	2.997	2.64	0.13	53.35	5.598	68.78
Return %	0.022	0.35	-5.43	10.03	18.861	566.54
Volume (millions of shares)	13.520	19.14	0.01	382.77	6.727	76.70
Natural log volume	8.663	0.98	3.14	12.28	-0.370	1.98
Volatility	0.040	0.01	0.01	0.14	1.653	17.43
EOD quoted spread	14.799	19.69	1.25	309.56	7.672	71.63
CS effective spread	149.23	30.57	45.23	665.22	3.153	35.08
AR effective spread	193.19	65.27	13.65	1825.3	13.735	314.27

France:						
Market capitalization, $ millions	2487.5	10200	1.34	131380	7.776	73.80
Local Currency Price	27.962	41.20	0.01	298.39	3.022	11.63
Price, $	34.341	50.89	0.02	395.26	3.111	12.56
Return %	0.126	1.38	-27.69	18.32	-5.586	234.03
Volume (millions of shares)	0.218	1.19	0.00	27.14	15.308	312.40
Natural log volume	1.684	2.39	-2.30	9.78	0.789	0.10
Volatility	0.033	0.02	0.01	0.28	4.534	36.47
EOD quoted spread	265.57	507.66	3.83	9018.1	8.401	113.84
CS effective spread	168.19	232.95	1.21	4569.7	10.492	166.48
AR effective spread	231.87	236.27	10.01	4147.6	8.164	107.53

Germany:						
Market capitalization, $ millions	2197.7	9195.9	0.00	100000	7.059	56.82
Local Currency Price	18.388	32.78	0.01	418.27	5.228	41.70
Price, $	22.431	39.64	0.01	470.57	5.103	39.16
Return %	0.416	7.81	-50.00	300.00	31.718	1211.7
Volume (millions of shares)	0.103	0.66	0.00	13.19	13.746	224.11
Natural log volume	1.271	1.92	-2.23	9.39	1.121	1.47
Volatility	0.074	0.10	0.01	0.73	3.185	11.33
EOD quoted spread	798.25	1560.3	4.06	20000	4.735	32.48
CS effective spread	450.14	883.35	30.04	7564.3	3.985	18.27
AR effective spread	639.29	1024.8	53.98	9559.1	3.562	15.25

(Table A1 continues on the next page)

(Table A1 continued)

	Mean	Std	Min	Max	Skew	Kurt
Hong Kong:						
Market capitalization, $ millions	1369.2	8242.4	2.60	213362	18.964	431.62
Local Currency Price	4.201	12.28	0.02	251.38	9.233	124.36
Price, $	0.539	1.58	0.00	32.28	9.236	124.40
Return %	0.032	0.37	-5.74	5.41	-1.293	99.88
Volume (millions of shares)	5.326	14.12	0.00	474.26	19.415	571.10
Natural log volume	6.755	1.46	1.19	11.90	-0.052	0.27
Volatility	0.052	0.02	0.00	0.20	1.086	3.39
EOD quoted spread	234.52	164.18	8.30	1909.1	1.654	7.78
CS effective spread	212.58	96.37	31.24	1278.3	2.591	17.13
AR effective spread	293.74	133.16	50.46	1413.8	1.637	7.05
Indonesia:						
Market capitalization, $ millions	681.85	2496.4	0.83	27856	8.110	72.37
Local Currency Price	1947.5	5435.0	54.75	82217	8.368	93.60
Price, $	0.168	0.49	0.00	7.53	8.474	95.05
Return %	0.119	0.65	-5.89	7.65	-0.300	54.79
Volume (millions of shares)	15.337	41.24	0.00	464.65	5.960	43.57
Natural log volume	6.234	2.62	-0.19	12.48	-0.015	-0.79
Volatility	0.053	0.03	0.01	0.22	1.825	5.28
EOD quoted spread	260.12	260.51	25.90	2112.5	2.863	11.24
CS effective spread	230.44	119.48	52.20	909.19	1.754	4.54
AR effective spread	321.35	181.91	69.18	1481.9	1.974	5.99
Italy:						
Market capitalization, $ millions	1377.6	5240.7	1.40	73040	8.505	91.03
Local Currency Price	6.464	11.36	0.01	153.35	6.890	68.63
Price, $	7.732	13.50	0.02	176.73	6.680	63.71
Return %	0.023	0.20	-1.09	2.17	2.402	33.25
Volume (millions of shares)	1.888	12.00	0.00	189.05	11.815	157.66
Natural log volume	3.759	2.35	-1.33	11.75	0.714	0.25
Volatility	0.036	0.02	0.00	0.16	2.432	12.15
EOD quoted spread	223.24	192.91	8.26	1348.1	1.963	5.14
CS effective spread	171.88	139.94	20.10	1443.3	4.752	28.98
AR effective spread	225.01	143.76	26.98	1369.0	3.827	20.17

(Table A1 continues on the next page)

(Table A1 continued)

	Mean	Std	Min	Max	Skew	Kurt
Japan:						
Market capitalization, $ millions	1505.0	6067.9	2.44	181230	13.153	279.09
Local Currency Price	1969.7	3227.4	2.27	49995	6.864	64.59
Price, $	19.710	35.42	0.02	469.60	7.198	67.74
Return %	0.069	0.37	-8.44	7.53	-5.837	301.99
Volume (millions of shares)	0.603	4.17	0.00	213.22	41.078	2026.0
Natural log volume	3.959	2.02	-2.30	12.06	0.203	-0.13
Volatility	0.029	0.02	0.00	0.50	11.021	212.29
EOD quoted spread	77.962	121.48	9.96	3696.9	15.648	353.83
CS effective spread	120.30	113.33	14.87	3651.1	16.259	380.83
AR effective spread	174.92	126.80	18.11	3764.8	13.770	291.15
New Zealand:						
Market capitalization, $ millions	538.53	988.96	0.83	6647.7	3.287	12.80
Local Currency Price	2.474	2.70	0.02	17.29	2.509	9.20
Price, $	1.805	1.98	0.01	12.47	2.555	9.45
Return %	0.254	0.97	-1.61	10.13	7.429	69.94
Volume (millions of shares)	0.365	0.74	0.00	7.56	6.329	56.22
Natural log volume	4.198	1.57	0.30	8.63	0.162	-0.43
Volatility	0.040	0.07	0.01	0.55	5.193	32.17
EOD quoted spread	611.01	1757.6	53.17	18095	7.730	68.27
CS effective spread	399.54	890.88	29.02	6666.7	5.060	28.69
AR effective spread	418.84	780.49	56.55	5822.0	4.949	29.10
Norway:						
Market capitalization, $ millions	938.81	4443.4	0.98	70556	12.373	179.88
Local Currency Price	53.331	150.24	0.30	2615.8	14.474	244.05
Price, $	7.285	19.45	0.05	330.92	13.567	221.11
Return %	0.153	0.72	-6.43	8.02	2.406	64.61
Volume (millions of shares)	0.332	0.92	0.00	8.85	5.469	36.31
Natural log volume	3.270	1.96	-1.30	8.73	0.272	-0.20
Volatility	0.047	0.03	0.01	0.21	2.220	6.72
EOD quoted spread	299.83	359.49	8.99	2902.8	3.301	14.80
CS effective spread	226.78	176.03	33.63	1290.6	2.865	10.58
AR effective spread	325.44	246.70	39.70	1922.2	3.063	12.93
Philippines:						
Market capitalization, $ millions	871.62	1944.3	0.00	14821	3.858	17.39
Local Currency Price	47.260	191.33	0.00	2197.7	7.982	73.75
Price, $	1.017	4.15	0.00	48.50	8.125	76.58
Return %	0.094	0.61	-5.36	5.93	0.111	56.07
Volume (millions of shares)	12.683	83.08	0.00	1311.5	13.667	207.71
Natural log volume	5.531	2.45	-0.85	12.58	-0.168	0.00
Volatility	0.046	0.03	0.01	0.26	2.605	12.95
EOD quoted spread	313.78	339.30	28.18	2887.5	2.713	12.20
CS effective spread	227.08	194.32	43.73	2488.9	6.030	62.85
AR effective spread	318.21	229.03	46.34	2515.8	3.927	29.66

(Table A1 continues on the next page)

(Table A1 continued)

	Mean	Std	Min	Max	Skew	Kurt
South Africa:						
Market capitalization, $ millions	1221.4	3912.0	0.00	55447	8.230	93.14
Local Currency Price	35.775	98.49	0.01	1604.2	10.203	148.75
Price, $	3.302	8.47	0.00	129.09	8.729	114.06
Return %	0.377	1.42	-4.63	14.38	5.376	39.79
Volume (millions of shares)	1.563	10.84	0.00	209.10	16.680	309.84
Natural log volume	4.616	1.87	-0.46	12.06	0.325	0.42
Volatility	0.067	0.08	0.01	0.69	4.027	20.46
EOD quoted spread	728.06	1094.1	16.70	8242.0	2.907	10.64
CS effective spread	460.54	737.94	33.99	6074.1	4.162	21.10
AR effective spread	562.54	794.83	39.78	6292.2	3.776	17.52
Thailand:						
Market capitalization, $ millions	575.26	1968.8	2.64	31700	8.398	95.87
Local Currency Price	24.132	78.34	0.20	1626.4	12.627	223.14
Price, $	0.750	2.44	0.01	50.52	12.605	221.83
Return %	0.037	0.25	-2.56	2.72	-0.214	45.96
Volume (millions of shares)	8.682	21.00	0.00	228.53	6.134	48.01
Natural log volume	6.178	2.46	-0.73	11.95	-0.517	-0.19
Volatility	0.031	0.02	0.01	0.30	6.321	70.32
EOD quoted spread	141.22	175.07	35.21	2750.0	7.259	78.03
United Kingdom:						
Market capitalization, $ millions	1674.7	8854.4	0.23	175070	10.885	146.20
Local Currency Price	250.13	565.59	0.03	9676.7	6.708	72.05
Price, $	3.683	8.22	0.00	141.92	6.719	73.02
Return %	0.066	0.86	-21.11	13.98	-2.995	228.81
Volume (millions of shares)	1.409	6.20	0.00	165.90	14.572	298.12
Natural log volume	4.213	2.11	-1.56	11.92	0.250	-0.25
Volatility	0.055	0.04	0.00	0.37	2.472	9.36
EOD quoted spread	666.05	737.14	2.59	5833.3	2.302	7.85
CS effective spread	259.94	239.59	13.04	3491.7	3.935	28.97
AR effective spread	359.87	327.84	21.76	3566.7	3.184	16.45