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

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Abstract: Machines dominate the trading process 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 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 greater 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

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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, with recalibration often occurring multiple times per day.

To shed new light on these questions, we examine a multi-year sample of stock trading in the U.S. and around the globe and report evidence that liquidity provision and consumption display sizable, economically relevant seasonal patterns undetected in previous work. Furthermore, we offer a behavioral rationale for these patterns, which is bolstered by research in both psychology and economics. 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 6.6% 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 three-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)).

Further, making use of high frequency metrics that reflect changes in trade informativeness and required compensation for inventory risk, we 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 (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 (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 (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 that 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 that 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 (Pulcu, Trotter, Thomas, Mc-

Farquhar, 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 study 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 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. That is, in the Northern Hemisphere spreads are widest in December, while in the southern hemisphere they are widest in May. 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.

Theory dating back to Stoll (1978), Ho and Stoll (1981, 1983), and Glosten and Milgrom (1985) suggests that the magnitude of liquidity costs (spreads) is determined in part by the impatience of informed traders and in part by the risk aversion of market makers. Market structure literature generally recognizes that impatient traders tend to shift their order mix away from non-marketable limit orders (which provide liquidity and do not require execution immediacy) to-

[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.

wards marketable limit orders (which demand liquidity and immediacy). Consequently, the marketable orders generated by informed traders adversely select market makers, increasing their operating costs and compelling them to charge more for liquidity. Using a standard high-frequency metric for gauging adverse selection costs – the price impact – we demonstrate a noticeable increase in price impact during the fall and winter months. This phenomenon aligns with the time of year when many people become susceptible to the effects of SAD.

To further substantiate the potential link between informed trader impatience and SAD, we use two additional metrics: the Informed Trading Intensity (ITI) developed by Bogousslavsky, Fos, and Muravyev (2023) and the Price Jump Ratio (PJR) proposed by Weller (2018). The ITI is a product of a machine learning technique trained to recognize informed traders within conventional datasets. It measures the rate with which information gets assimilated into prices and has two sub-variations: ITI patient and ITI impatient. The former captures the extent of market participation by informed traders, who do not place much emphasis on immediacy, while the latter picks up the activity of those who seek to trade promptly. Our data reveal a negative association between ITI patient and SAD, while ITI impatient has a positive association with SAD. This result reinforces our hypothesis that informed traders exhibit reduced patience during the fall and winter months, thereby intensifying adverse selection pressure on market makers.

The PJR, on the other hand, is a metric that gauges the effectiveness with which information is integrated into prices. Weller (2018) argues that if informed traders are successful in incorporating earnings information prior to earnings announcements, price reactions to the actual announcements should be less pronounced. Additionally, Brogaard, Hendershott, and Riordan (2019), Hagströmer and Menkveld (2023), and Kwan, Philip, and Shkilko (2023) demonstrate that individual marketable orders transmit information into prices more effectively than individual non-marketable orders. In our context, if informed traders transition from non-marketable to marketable orders during the fall and winter months when their patience decreases, the process of information assimilation into prices should gain efficiency. The data corroborate this notion;

the PJRs become noticeably smaller during the fall and winter months.

Turning to risk aversion, we rely on a standard market structure metric, the realized spread, to assess fluctuations in inventory costs imposed on those seeking liquidity by the market makers. In the process of providing liquidity, market makers accumulate long and short stock positions, referred to as inventories. Holding inventories over extended periods of time is costly due to the risk of price fluctuations that market makers must shoulder. If market maker risk aversion follows seasonal patterns, it stands to reason that greater compensation would be sought for bearing inventory risk during months characterized by heightened risk aversion. The data support this possibility, with realized spreads reaching peak levels the influence of SAD is most pronounced.

Our study contributes to several strands of market structure literature that examine the impacts of automation on liquidity costs and price discovery. O'Hara (2015), Easley, Lopez de Prado, O'Hara, and Zhang (2020), and Shkilko and Sokolov (2020) describe the contemporary trading landscape as highly automated and ultra-fast, where human abilities to react and process information are substantially surpassed by those of machines. Hendershott, Jones, and Menkveld (2011) and Brogaard, Hagströmer, Nordén, and Riordan (2015) show that automation often leads to significant reductions in both price impacts and realized spreads, as algorithms are more efficient in avoiding adverse selection and managing inventory. Consequently, automation is often associated with an overall reduction in liquidity costs. Particularly notable in our context, Chakrabarty and Moulton (2012), Chakrabarty, Moulton, and Wang (2022) show that another important advantage of this new world is the significant reduction of human attention constraints, ultimately leading to more efficient market making. It nonetheless remains unclear whether automation has entirely eliminated the impacts of human behavior on the trading process.

Accordingly, our findings shed new light on the extent of automation reducing human effects in liquidity provision and demand. While the use of machines is certainly widespread and pervasive, the influence 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 incidence 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 Liquidity and impatience metrics

When analyzing the U.S. sample, we rely on conventional high-frequency metrics of displayed liquidity and trading costs. To examine displayed liquidity, we estimate the *quoted spread* as the difference between the lowest offer and the highest bid across all exchanges. Regulation requires that liquidity-seeking buy orders be sent to the exchange with the lowest offer quote (the National Best Offer) and sell orders to the exchange with the highest bid quote (the National Best Bid). Quoted spreads, often called the bid-ask spreads or National Best Bid and Offer (NBBO) spreads, capture liquidity costs based on posted prices and are among the most commonly studied liquidity metrics.

In addition to quoted spreads, market structure research often estimates quoted depths at the NBBO quotes, which represent the average number of shares available between the best bid and the best offer. When market making costs increase, quoted spreads typically increase, while quoted depths decline as market makers aim to put up smaller amounts of capital at risk. It should be noted that TAQ data do not allow researchers to compute total quote depths, that is, the total number of shares available at the best quotes at a given time. Instead, the data contain enough information to gauge the size of a typical quote posted at the best prices. For our purposes, total depths and quote sizes are generally interchangeable.

Although posted prices are commonly used as benchmarks, many traders time liquidity, demanding it when it is relatively cheap. Consequently, they often obtain average execution prices that are better than average posted quotes. In addition, execution prices may be better due to better-priced hidden liquidity or price improvement offered by liquidity providers. Still in some cases, liquidity demanders may receive prices worse than those posted, particularly if their demand exceeds the quantities posted at the best quotes. With these nuances in mind, we measure the actual trading costs incurred by liquidity demanders by computing the *effective spread*. This metric is calculated as the difference between the traded price and the quote midpoint at the time of the trade for purchases and as the difference between the midpoint and the traded price for sales.

In market structure research, quote midpoints are computed as averages between the best bid and ask prices. Conventionally, they are considered representations of the stock's intrinsic value at a given moment. For instance, if the quoted spread is \$9.98 on the bid and \$10.00 on the offer, the midpoint is \$9.99. A buyer who executes at \$10.00 pays \$0.01 per share more than the intrinsic value. The \$0.01 amount is the effective spread or the cost the buyer is willing to incur in exchange for immediacy.

The TAQ data do not directly distinguish between the buyer-initiated and seller-initiated trades. As is common, we infer trade direction using the Lee and Ready (1991) algorithm. This algorithm posits that trades with prices greater than the midpoint are likely buyer-initiated because impatient buyers are willing to pay for liquidity by accepting prices slightly above intrinsic values. Conversely, trades with prices below the midpoint are likely seller-initiated. For a small number of trades executed at midpoint prices, the algorithm copies the initiator from the previous trade. Despite its development in the early 1990s, the algorithm continues to be widely used today. Chakrabarty, Pascual, and Shkilko (2015) demonstrate its continued high efficacy in modern high-speed markets.

Early market structure research argues that informed traders tend to be impatient as they compete with others to incorporate short-lived information into prices (e.g., Glosten and Milgrom (1985), Kyle (1985)). Such traders use market and marketable orders that demand liquidity and immediacy. More recent studies show that the informed may also use limit orders, thus supplying liquidity (e.g., Kumar and Seppi (1994); Kaniel and Liu (2006); Goettler, Parlour, and Rajan (2009), Brolley and Malinova (2017), Roşu (2020), Bhattacharya and Saar (2021), Riccó, Rindi, and Seppi (2022)). When the informed seek liquidity, their trades push quotes in the direction of their information. Conversely, when they provide liquidity, quotes adjust in the direction of information without trades.

An impatient informed buyer typically places marketable buy orders until the price rises to a level at which further purchasing becomes unprofitable. The trades resulting from such orders are said to generate *price impact*. For seller-initiated trades, price impact is computed as the difference between the quote midpoint at the time of the trade and a future midpoint. For buyer-initiated trades, price impact is computed as the difference between a future midpoint and the midpoint at the time of the trade. In modern high-speed markets, quotes adjust to trades quickly, so we use a 60-second horizon for future midpoints. We, however, recognize that in a sample of over 900 securities, there are bound to be a few that have longer midpoint adjustment periods, so we use an additional 300-second horizon for robustness.

Price impacts hold significant importance in our analyses, as we anticipate them to increase when informed traders affected by SAD and winter blues display greater impatience during late fall and winter. In addition to capturing impatience, price impacts represent an important market-making cost that factors into quoted and effective spreads. Known as *adverse selection*, it denotes the loss a market maker incurs while offering liquidity to an informed market participant. For illustrative purposes, consider a scenario where at t_0, the bid and offer quotes are \$9.99 and \$10.00, respectively. An informed trader purchases at the offer, driving the quotes up to \$10.01 and \$10.02 by t_1. A market maker who sold to the trader at \$10.00 needs to close her position but can only do so at \$10.01 or higher, thus incurring a loss of 1 cent or more per share.[3] Consequently, more impatient informed trading during the fall and winter will likely prompt market makers to widen spreads, compensating for the amplified adverse selection cost.

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

[3] If the market maker closes the position while providing liquidity at \$10.01, her loss is 1 cent per share. If she is impatient, she closes the position by demanding liquidity at \$10.02, losing 2 cents per share.

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.

Adverse selection is an important cost, but not the only one, incurred by market makers. Others include inventory and fixed costs. Inventory costs arise from non-zero inventory positions due to changes in asset prices. For example, when a market maker acquires a long position from a seller, even if the seller is uninformed, the position may lose value over time if the asset price falls. Market makers factor in the expected value of such losses and the liquidity costs of closing inventory positions into the liquidity price. In turn, fixed costs primarily represent the expenses on sophisticated technology required for market making.

Capturing these two costs separately is not feasible using standard microstructure datasets. Consequently, the literature estimates them jointly as *realized spreads*, computed as the difference between effective spreads and price impacts. In addition to reflecting inventory and fixed costs, realized spreads also include market making profits (e.g., Hendershott, Jones, and Menkveld (2011) and Brogaard, Hagströmer, Nordén, and Riordan (2015)). As we mentioned earlier, SAD and winter blues tend to cause both increased impatience and risk aversion. Both these factors may affect realized spreads in our context. First, heightened impatience might prompt market makers to seek quicker ways to close out inventory positions, leading to greater position management costs and hence realized spreads. Second, increased risk aversion may necessitate greater compensation for the expenses and risks associated with market making also resulting in larger realized spreads.

When computing the high-frequency metrics, we follow the procedure suggested by Holden and Jacobsen (2014). In addition, all high-frequency metrics are scaled by the corresponding quote midpoints to allow for comparability in the cross-section. Also, to make the effective and realized spreads, as well as price impacts, visually comparable to the quoted spreads, we multiply them by two. Finally, we 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 \$14.709 billion and trades at \$51.03 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 \$2.76 billion in the 25$^{\text{th}}$ percentile and over \$13.7 billion in the 75$^{\text{th}}$ 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 7.46 bps, while the average effective spread is 5.79 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 4.27 bps and increases to 4.63 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 1.16 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.

While we have high-frequency data for the U.S., our liquidity analyses extend to other countries, where we must rely on low-frequency daily data. The literature has put forth several low-frequency liquidity proxies, including the end-of-day quoted spread denoted as EOD, which is computed as the difference between the closing bid and ask quotes scaled by the midpoint of these quotes. Additionally, two low-frequency estimators, as proposed by Corwin and Schultz (2012) and Abdi and Ranaldo (2017), named *CS* and *AR* respectively, have been shown to correlate with effective spreads. Notably, Abdi and Ranaldo (2017) demonstrate that the *EOD* quoted spread is the most accurate low-frequency liquidity proxy. Still, given that our high-frequency metrics differentiate between quoted and effective spreads, we include *CS* and *AR* alongside *EOD* for the sake of completeness.

The lower section of Table 1 contains three low-frequency liquidity metrics for the U.S. sample. In a later section, we demonstrate that these metrics successfully capture the SAD effects, similar to the high-frequency metrics, which enables us to extend the analysis to non-U.S. markets. We note that it is common for the low-frequency metrics to have magnitudes distinct from their high-frequency counterparts. The former metrics were designed to capture time-series and cross-sectional variations in liquidity, rather than precisely represent the true spread values. Jahan-Parvar and Zikes (2022) find that *CS* and *AR* frequently yield estimates that are considerably larger than those from high-frequency data. Our data align with this finding. While the *EOD* quoted spread closely resembles in magnitude its high-frequency counterpart (i.e., 5.76 bps compared to 7.46 bps), the *CS* and *AR* estimates are 96.27 and 64.62 bps respectively. It is important to reiterate that while the magnitude of these estimates is not the primary focus of our analyses, their ability to capture fluctuations in liquidity costs over time is crucial. As we demonstrate in a subsequent section, all three metrics perform well for this purpose.

2.2 SAD Incidence

To create the SAD Incidence variable, which we use to model the seasonal pattern in market participant impatience and 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 America and recorded the date when each patient's SAD symptoms first arose 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.[4]

The SAD Incidence variable reflects the stock of people who are actively experiencing SAD symptoms, including heightened impatience and risk aversion, and so we use SAD Incidence as a proxy for seasonal variation in these variables. 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 which we produce as follows. After using a spline function to smoothly interpolate the monthly SAD Incidence variable to daily frequency, 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.

[4] 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.

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 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 this possibility by plotting monthly estimates of the effective spread (top plot) and quoted spread (bottom plot). Effective spreads appear in orange, quoted spreads appear in black, 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. 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.

In both plots, the 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 impatience and risk aversion captured by SAD Incidence. The magnitude of the 0.29 bps seasonal variation in the effective spread represents variation of 5.0% (= 0.29/5.79) relative to the mean effective spread, and the seasonal change in the quoted spread, 0.49 bps, represents a 6.6% (= 0.49/7.46) difference relative to the mean quoted spread.

[Figure 1]

Whereas the results in Figure 1 are suggestive of a seasonal connection between SAD Incidence and spreads, they do not account for the well-known trading cost determinants such as volume and volatility. Hendershott, Jones, and Menkveld (2011), O'Hara and Ye (2011), and Brogaard, Hagströmer, Nordén, and Riordan (2015) report strong associations between these two variables and trading costs and therefore using them as controls appears warranted. More specifically, greater volatility is often associated with greater adverse selection and therefore greater trading costs, while greater volume is associated with the possibility of more effective inventory management and therefore lower trading costs. To address this issue, we conduct more formal analysis by estimating the following regression model for each stock i on each day t:

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

where $DepVar$ is the quoted spread, quoted depth, effective spread, price impact, or realized spread, SAD is SAD Incidence, $Volume$ is the lagged natural logarithm of daily volume, and $Volatility$ is the lagged quote-based intraday volatility (expressed as a standard deviation).[5] 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 quoted and effective spreads as well as quoted depths vary with SAD Incidence, which captures the effects of both risk aversion and impatience, both of which we hypothesize influence the costs and risks of liquidity provision. The quoted spreads increase by 0.416 bps and the effective spreads increase by 0.233 bps in Base regressions (columns [1] and [5]); estimates are similar in Full regressions that control for the effects of volume and volatility (columns [2] and [6]). When it comes to quoted depth (columns [3] and [4]), it decreases consistently with our expectations. We note that the economic magnitude of the changes in spreads is consistent with that observed in univariate results, albeit it is more moderate likely due to controlling for volume and volatility. Specifically,

[5] Our results are qualitatively unchanged if instead we use an alternate measure of volatility based on the lagged difference between the highest and lowest price of the day scaled by the average of the two prices and multiplied by 100.

quoted spreads vary by 5.2% (= 0.416 × 0.94/7.46) and effective spreads by 3.8% (= 0.233 × 0.94/5.79).[6] 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. The results in Table 3 are consistent with our expectations; both price impacts and realized spreads increase with SAD Incidence.

[Table 3]

In Panel A, the price impacts measured at the 60-second horizons increase by 0.104 bps and those measured at 300-second horizons increase by 0.105 bps in the Base models in columns [1] and [3]. This translates into an economically large seasonal variation of 2.3% (= 0.104 × 0.94/4.27) for the 60-second case and 2.1% (= 0.105 × 0.94/4.63) 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 Incidence variable 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 and 300-second realized spreads increase by 0.128 bps in the Base models and increase similarly in Full 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

[6]The economic magnitudes are calculated as the coefficient estimate times the range of the SAD variable (roughly 0.94) divided by the mean spread value from Table 1.

economic magnitudes are large. For the 60-second realized spread, the seasonal variation relative to the mean amounts to 8.0% (= 0.128 $\times$ 0.94/1.51), and for the 300-second realized spread, the economic magnitude is 10.4% (= 0.128 $\times$ 0.94/1.16).

3.2 Informed trading intensity

Our analysis of price impacts assumes that informed traders become less patient when affected by SAD and switch from non-marketable to marketable limit orders. Until recently, confirming this assumption without proprietary data would have been impossible. However, a recent study by Bogousslavsky, Fos, and Muravyev (2023) proposes a new set of metrics that allows researchers to gauge the patience with which informed traders open their positions. They train a machine learning algorithm to recognize informed trading using an observed sample of activist investor trades and obtain a set of non-linear combinations of variables that determine the prevalence of informed trading. Subsequently, they use these variable combinations to compute informed trading intensity (ITI) for the universe of stock-days. Importantly, they obtain two additional metrics based on periods when activist investors trade patiently and periods when they trade impatiently, pressed for time to open the desired positions.

Table 4 examines how the three ITI metrics correlate with the SAD variable.[7] We expect that as a measure of general informed trading, ITI should not exhibit a significant relationship with the SAD variable. After all, the number of news events and their price-relevance should not vary seasonally. However, we expect ITI patient (impatient) to decrease (increase) during the months with the highest SAD incidence. The data confirm our expectations; while ITI does not change, ITI patient declines, and ITI impatient increases during the months with the highest numbers of SAD cases.

[Table 4]

[7] We thank Dmitriy Muravyev for sharing the ITI data with us.

3.3 Information incorporation into prices

As market participants research firm fundamentals, value-relevant information flows into prices through their trading. The more impatient such market participants are, the more direct price pressure they create, and the more likely prices will reflect their information. In the case of earnings, the more information is incorporated into prices prior to an announcement, the smaller should be the market reaction to the announcement itself. To measure this effect, Weller (2018) introduces the price jump ratio, PJR, that divides the earnings announcement return by the total return plausibly attributable to the announcement. The latter includes three weeks of pre-announcement price changes. A low PJR is consistent with high levels of price discovery, as it implies that a substantial portion of earnings information is incorporated into prices in the weeks prior to the announcement. In our setting, if informed trader impatience indeed increases in SAD, PJR should decline during the fall and winter months.

To compute PJR, we follow Weller (2018) and let T be the earnings announcement date. We then define the *announcement window* as $[T-1, T+2]$, *event window* as $[T-21, T+2]$, and *pre-event window* as $[T-255, T-90]$. For each day t and each stock i, we compute the close-to-close return, r_{it}, and the return on each the market index, r_{mt}. We then obtain the abnormal return, abr_{it}, as the difference between the stock i return on day t and the expected return according to the market model estimated in the pre-event window, that is,

$$abr_{it} = r_{it} - \hat{\alpha}_i - \hat{\beta}_i r_{mt}. \tag{2}$$

Next, we define cumulative abnormal return as the sum of abnormal returns from t_1 to t_2,

$$CAR_i^{t_1,t_2} = \sum_{t=t_1}^{t_2} abr_{it}, \tag{3}$$

and compute PJR as the ratio of the announcement-window CAR and the event-window CAR,

$$PJR_i = \frac{CAR_i^{T-1,T+2}}{CAR_i^{T-21,T+2}}. \tag{4}$$

One notable implementation issue when computing PJR is that the denominator of the metric may occasionally be close to zero. To account for this issue, Weller (2018) drops the announcements for which the absolute event-window CAR is smaller than $\sqrt{24}\sigma_i$, where σ_i is the standard deviation of r_i over the preceding month. We do the same.

To reiterate, if informed investors shift their order submissions from non-marketable to marketable limit orders due to increased impatience induced by SAD, we anticipate a more efficient incorporation of information into prices. This anticipation is grounded in recent literature on price discovery, which demonstrates that individual marketable orders carry more information into prices compared to individual non-marketable orders (e.g., Brogaard, Hendershott, and Riordan (2019), Hagströmer and Menkveld (2023), Kwan, Philip, and Shkilko (2023)). The results presented in Table 4 align with our expectations. As informed trading becomes less patient during late fall and winter, information is incorporated into prices more efficiently, resulting in smaller PJRs.

3.4 Low-frequency liquidity metrics

In a later section, we expand our analysis to international markets because the magnitude of the SAD effect and 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 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 2 shows that seasonal correlations between the low-frequency metrics and the SAD Incidence variable closely resemble those identified earlier for the high-frequency spread metric. That is, both the low-frequency metrics and the SAD Incidence variable dip in late spring and peak in late fall.

[Figure 2]

In turn, the equation 1 results in Table 5 confirm that all three proxies vary with the SAD Incidence 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 the lack of power to identify the SAD effect here. The magnitude of the seasonal changes are again large: 0.190 bps (or 3.1% = $0.190 \times 0.94/5.76$ relative to the unconditional mean) for the end-of-day quotes, 4.303 bps (4.2% = $4.303 \times 0.94/96.27$ relative to the unconditional mean) for the Corwin-Schultz spreads, and 3.529 bps (5.1% = $3.529 \times 0.94/64.62$ relative to the unconditional mean) for the Abdi-Ranaldo spreads. 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.

[Table 5]

3.5 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 6. The largest group of firms has a mean size above $28 billion, and the smallest below $2.4 billion. The high- and low-frequency liquidity cost metrics are consistently smallest for tercile 1 and increase as firm size decreases. This result is anticipated, as the costs related to providing liquidity are higher in smaller stocks due to increased information asymmetries, longer inventory holding periods, and elevated fixed costs per share resulting from lower trading volumes (e.g., Dyhrberg, Shkilko, and Werner (2023)).

[Table 6]

We examine the relationship between SAD and the various liquidity metrics for each of the terciles in Tables 7 and 8. With an increase in SAD Incidence, as impatience and risk aversion rise, we anticipate that price impacts and realized spreads will increase more in the stocks where they hold greater significance. For instance, in small stocks where information asymmetries are relatively high and informed traders' incorporation of information into prices is more pronounced, a rise in the impatience of informed traders should lead to a larger increase in price impacts compared to their larger counterparts, where information asymmetries are lower. Likewise, in the case of small stocks where trading volumes remain relatively low and managing inventory proves to be more challenging, an increase in risk aversion should lead to a more substantial increase in the expected compensation for incurring inventory costs also known as the inventory penalty function (Aït-Sahalia and Sağlam (2017)).

Price impact and realized spreads appear in Table 7. As expected, 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 by 0.022 bps, 0.117 bps, and 0.195 bps for the large through small terciles, respectively, with similar figures for the 300-second horizons. Statistical significance of the SAD coefficient is observed at the 5% level or better for all but the largest-firm tercile.

[Table 7]

Table 8 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 variable in all cases. The increases are consistently smallest for the largest-firm tercile, and tercile 2 increases are smaller than tercile 3 increases. Overall, consistent with our expectations, the tercile results suggest that the impatience and risk aversion associated with SAD have greater economic impact on the spreads of smaller firms compared to larger firms.

[Table 8]

3.6 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 9; more granular summary statistics, on a country-by-country basis, are tabulated in an online appendix (Table A1).

[Table 9]

Starting with the stock characteristics in Table 9, we see the average firm market capitalization, converted to U.S. dollars, is over $1.6 billion for the northern temperate zone and northern subtropic groupings, and is a little 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), while the southern sub-tropics/temperate region has the most volatile volume of shares traded. In contrast, the northern temperate zone has the lowest share volume (683 million), and the northern sub-tropics has the lowest share volume volatility. Because the international quote-based intraday volatility data are not readily available to us, we calculate volatility as the difference between the high and low prices of the day scaled by their average and multiplied by 100. The return volatility distributions are fairly similar to each other across the latitude zones, but are not directly comparable to the US volatility distribution due to the different calculation methods.

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 metrics tend to be smaller for the northern regions, with mean values between 89 and 533 bps in those regions.

Turning to formal analysis of the spreads, we estimate equation 1 for each of the four regions. Results appear in Table 10. 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 Incidence variable. For the southern region, we shift the SAD Incidence 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.

[Table 10]

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 0.177 bps, CS spreads by 2.163 bps, and AR spreads by 2.420 bps, although the EOD coefficient lacks significance at conventional levels. In Panels B and C, the northern sub-tropics and tropics, we find no discernible SAD effect. This is expected in light of the fact that medical research finds the effects of SAD are most noticeable at latitudes above 40 degrees. 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 Incidence 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.

4. Conclusion

We live in a world increasingly influenced by technology. In financial markets, computers execute trades at speeds that exceed a human's ability to process information. While early research highlights substantial effects of human cognitive constraints on the trading process, studies of modern automated markets propose that these constrains may have diminished in their former significance.

We ask whether human behavior continues to play a role in the generation and consumption of liquidity using seasonal fluctuations in impatience and risk aversion linked to the prevalence of Seasonal Affective Disorder (SAD) during the fall and winter months. We begin by examining liquidity costs 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. Price impacts and realized spreads reach their peaks during late fall and winter, and they are at their lowest during late spring and summer. Since these two metrics serve as proxies for the costs of market making, liquidity costs (spreads) naturally mirror the same pattern.

Notably, two metrics that aid in assessing the intensity and effectiveness of information incorporation into prices – the Informed Trading Intensity and the reciprocal of the Price Jump Ratio – likewise experience an increase during the months when the population is affected by SAD. Consequently, in a manner consistent with the familiar trade-offs inherent in market structure, enhancements in price discovery are associated with higher liquidity costs.

Lastly, in cross-sectional analyses, we observe that the seasonal effects are most pronounced for small firms consistent with the idea that such firms have the greatest information asymmetries and the highest inventory holding risks. 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 that human nature influences liquidity through seasonally varying daylight exposure. Our findings suggest that 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 influence on the trading process 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. 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	14,709	29,121	5,509	2,760	13,785
Price, $	51.03	41.56	42.27	27.56	61.41
Volume, thousands of shares	2,594	5,160	1,270	615	2,832
Natural log volume	12.30	2.11	12.59	11.10	13.74
Volatility	11.58	37.40	8.13	5.36	11.79
High-frequency liquidity metrics, bps:					
Quoted spread	7.46	16.71	5.31	3.61	7.91
Effective spread	5.79	11.51	4.30	2.91	6.09
Price impact, 60s	4.27	2.57	3.77	2.66	5.04
Price impact, 300s	4.63	3.36	3.96	2.68	5.41
Realized spread, 60s	1.51	9.89	0.40	0.14	1.03
Realized spread, 300s	1.16	9.23	0.30	0.14	0.67
Low-frequency liquidity metrics, bps:					
EOD quoted spread	5.76	16.26	3.41	2.44	5.54
CS effective spread	96.27	34.53	87.75	72.16	110.86
AR effective spread	64.62	20.73	60.38	50.11	73.77

Table 2
SAD, Displayed Liquidity, and Trading Costs

The table examines the relationship between the SAD Incidence variable, quoted spreads, quoted depths, and effective spreads. The sample period spans January 2010 through December 2019. The reported coefficients are obtained from the regression of the following form:

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

DepVar is the effective or quoted spread, or quoted depth in stock i on day t, *SAD* is SAD incidence, *Volume* is the lagged natural logarithm of daily number of shares traded, and *Volatility* is the lagged quote-based intraday volatility (expressed as a standard deviation). In specifications [1], [3], and [5], we report the results from the Base models that do not include the control variables. In specifications [2], [4], and [6], 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		Quoted depth		Effective spread	
	Base	Full	Base	Full	Base	Full
	[1]	[2]	[3]	[4]	[5]	[6]
SAD	0.416***	0.326***	-2.036***	-2.378***	0.233***	0.167***
	(0.06)	(0.07)	(0.71)	(0.70)	(0.04)	(0.05)
Volatility		0.122***		0.011		0.085***
		(0.03)		(0.02)		(0.02)
Volume		-0.650***		10.019***		-0.399**
		(0.25)		(1.67)		(0.18)
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Adj. R^2	0.64	0.67	0.67	0.67	0.62	0.65

Table 3
SAD and Trading Cost Components

The table examines the relation between SAD Incidence 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:

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

DepVar is the price impact or realized spread in stock i on day t, *SAD* is SAD Incidence, *Volume* is the lagged natural logarithm of daily number of shares traded, and *Volatility* is the lagged quote-based intraday volatility (expressed as a standard deviation). 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	0.104***	0.068**	0.105***	0.067**
	(0.03)	(0.03)	(0.03)	(0.03)
Volatility		0.029***		0.036***
		(0.01)		(0.01)
Volume		0.368***		0.171***
		(0.05)		(0.06)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Adj. R^2	0.48	0.49	0.44	0.45

Panel B: Realized spreads				
SAD	0.128***	0.099***	0.128***	0.100***
	(0.03)	(0.03)	(0.03)	(0.03)
Volatility		0.056***		0.048***
		(0.01)		(0.01)
Volume		-0.757***		-0.563***
		(0.16)		(0.14)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Adj. R^2	0.58	0.61	0.52	0.55

Table 4
Informed Trading Intensity and Information Incorporation into Prices

The table examines the relationship between the SAD variable, three proxies for informed trading intensity (ITI) proposed by Bogousslavsky, Fos, and Muravyev (2023), and the price jump ratio (PJR) proposed by Weller (2018). The ITI proxies are obtained using a machine learning technique trained on a sample of informed institutional transactions and extrapolated to the entire stock-day universe. *ITI* is the proxy for all informed trading, whereas *ITI patient* and *ITI impatient* distinguish between patient and impatient informed trading. In turn, PJR is computed as the return immediately surrounding an earnings announcement divided by the return that includes three weeks preceding the announcement,

$$PJR_i = \frac{CAR_i^{T-1,T+2}}{CAR_i^{T-21,T+2}},$$

where $CAR_i^{T-1,T+2}$ is the cumulative market-adjusted return for the announcement i from day $T-1$ to day $T+2$, with T being the announcement date, and $CAR_i^{T-21,T+2}$ is the same metric computed from day $T-21$ to day $T+2$. The sample period spans January 2010 through December 2019. The reported coefficients are obtained from the regression of the following form:

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

DepVar is one of the three above-mentioned ITI metrics or the PJR metric in stock i on day t, *SAD* is SAD Incidence, *Volume* is the lagged natural logarithm of daily number of shares traded, and *Volatility* is the lagged quote-based intraday volatility (expressed as a standard deviation). For each dependent variable, we report the results from the Base regression model, which does not include the control variables, and the Full model, which 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 ITI sample contains over 1.4 million stock-day observations, whereas the PJR sample is stock-earnings announcement based and therefore contains fewer, 95.5 thousand, observations.

	ITI		ITI patient		ITI impatient		PJR	
	Base	Full	Base	Full	Base	Full	Base	Full
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
SAD	0.003	0.001	-0.002	-0.004**	0.011***	0.009***	-2.527***	-3.241***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.97)	(0.87)
Volatility		0.003***		0.000		0.002		0.012***
		(0.00)		(0.00)		(0.00)		(0.00)
Volume		0.054***		0.042***		0.063***		8.912***
		(0.01)		(0.01)		(0.01)		(0.69)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Adj. R^2	0.03	0.07	0.02	0.05	0.03	0.012	0.10	0.09

Table 5
SAD and Low-Frequency Liquidity Metrics

The table examines the relation between the SAD Incidence 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:

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

DepVar is one of the three above-mentioned low-frequency metrics in stock i on day t, *SAD* is SAD Incidence, *Volume* is the lagged natural logarithm of daily number of shares traded, and *Volatility* is the lagged quote-based intraday volatility (expressed as a standard deviation). 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
	[1]	[2]	[3]	[4]	[5]	[6]
SAD	0.190***	0.114**	4.303***	3.326***	3.529*	2.765
	(0.05)	(0.05)	(1.34)	(1.22)	(2.04)	(2.01)
Volatility		0.092***		0.394**		0.556***
		(0.01)		(0.17)		(0.08)
Volume		-0.274		26.326***		13.741***
		(0.19)		(1.85)		(1.61)
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Adj. R^2	0.54	0.55	0.19	0.23	0.05	0.06

Table 6
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. 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	28,077	36,746	16,938	11,588	27,517
Price, $	70.36	49.92	58.54	40.02	83.04
Volume, thousands of shares	4,241	7,759	2,359	1,344	4,326
Volatility	5.93	4.67	5.32	3.95	6.72
High-frequency liquidity metrics, bps:					
Quoted spread	4.10	3.31	3.34	2.73	4.58
Effective spread	3.31	2.66	2.73	2.22	3.58
Price impact, 60s	2.94	1.68	2.53	2.06	3.34
Price impact, 300s	2.96	1.81	2.50	2.03	3.36
Realized spread, 60s	0.37	1.64	0.16	0.05	0.41
Realized spread, 300s	0.35	1.45	0.20	0.08	0.40
Low-frequency liquidity metrics, bps:					
EOD quoted spread	3.21	4.83	2.21	1.77	3.23
CS effective spread	84.59	25.32	80.00	67.09	97.52
AR effective spread	58.22	31.01	54.25	45.43	64.66

Panel B: Tercile 2

	Mean	St. dev.	Median	25th	75th
Stock characteristics:					
Market capitalization, $ millions	6,054	3,211	5,472	4,137	7,246
Price, $	50.85	42.46	42.41	27.35	61.04
Volume, thousands of shares	2,553	4,312	1,165	641	2,390
Volatility	8.97	4.92	8.22	6.30	10.19
High-frequency liquidity metrics, bps:					
Quoted spread	8.80	67.72	5.05	4.01	6.88
Effective spread	7.52	67.35	4.12	3.26	5.58
Price impact, 60s	4.13	1.91	3.73	3.00	4.72
Price impact, 300s	4.84	12.21	3.92	3.04	5.06
Realized spread, 60s	2.65	47.91	0.36	0.11	0.87
Realized spread, 300s	2.35	46.63	0.25	0.04	0.61
Low-frequency liquidity metrics, bps:					
EOD quoted spread	5.99	33.34	3.26	2.56	4.99
CS effective spread	99.42	40.68	90.38	72.63	116.02
AR effective spread	68.09	36.29	62.66	49.38	78.18

(Table 6 continues on the next page)

(Table 6 continued)

Panel C: Tercile 3					
	Mean	St. dev.	Median	25th	75th
Stock characteristics:					
Market capitalization, $ millions	2,449	1,541	2,256	1,736	2,825
Price, $	33.29	35.69	27.01	15.84	41.02
Volume, thousands of shares	2,026	4,271	778	388	1,734
Volatility	16.85	48.93	12.01	9.10	15.35
High-frequency liquidity metrics, bps:					
Quoted spread	10.80	21.17	7.78	5.80	11.38
Effective spread	8.35	14.49	6.03	4.72	9.04
Price impact, 60s	5.85	2.95	5.02	4.03	6.96
Price impact, 300s	6.48	3.87	5.52	4.26	7.59
Realized spread, 60s	2.49	12.68	0.87	0.36	1.99
Realized spread, 300s	1.86	11.85	0.55	0.16	1.36
Low-frequency liquidity metrics, bps:					
EOD quoted spread	8.56	20.88	5.28	3.83	9.14
CS effective spread	115.88	46.88	104.69	83.28	140.13
AR effective spread	77.85	32.92	71.29	57.58	94.60

Table 7
Cross-Sectional Results: SAD and Trading Cost Components

The table examines the relationship between SAD Incidence 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:

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

DepVar is the effective or quoted spread in stock i on day t; *SAD* is the SAD Incidence variable; *Volume* is the lagged natural logarithm of daily number of shares traded; and *Volatility* is the lagged quote-based intraday volatility (expressed as a standard deviation). 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 730,000 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	0.042**	0.034*	0.022	0.031
	(0.018)	(0.019)	(0.021)	(0.020)
Volatility	0.030**	0.036**	0.046	0.038
	(0.012)	(0.017)	(0.035)	(0.028)
Volume	0.304***	0.235***	-0.284*	-0.216
	(0.036)	(0.047)	(0.165)	(0.151)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Adj. R^2	0.56	0.45	0.42	0.28

(Table 7 continues on the next page)

(Table 7 continued)

Panel B: Tercile 2				
	Price impact, 60s	Price impact, 300s	Realized spread, 60s	Realized spread, 300s
	[1]	[2]	[3]	[4]
SAD	0.082***	0.086***	0.117***	0.113***
	(0.029)	(0.029)	(0.020)	(0.018)
Volatility	0.029***	0.031***	0.013***	0.012***
	(0.006)	(0.006)	(0.004)	(0.004)
Volume	0.373***	0.235***	-0.382***	-0.244***
	(0.030)	(0.037)	(0.031)	(0.027)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Adj. R^2	0.53	0.49	0.61	0.32

Panel C: Tercile 3				
	Price impact, 60s	Price impact, 300s	Realized spread, 60s	Realized spread, 300s
	[1]	[2]	[3]	[4]
SAD	0.086*	0.090*	0.195**	0.189**
	(0.046)	(0.052)	(0.080)	(0.076)
Volatility	0.025***	0.032***	0.055***	0.048***
	(0.009)	(0.011)	(0.009)	(0.008)
Volume	0.384***	0.062	-1.430***	-1.112***
	(0.111)	(0.144)	(0.295)	(0.278)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Adj. R^2	0.38	0.34	0.62	0.56

Table 8
Cross-Sectional Results: SAD, Displayed Liquidity and Trading Costs

The table examines the relationship between SAD Incidence 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:

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

DepVar is the effective or quoted spread in stock i on day t, *SAD* is the SAD Incidence variable, *Volume* is the lagged natural logarithm of daily number of shares traded, and *Volatility* is the lagged quote-based intraday volatility (expressed as a standard deviation). 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	0.153***	0.062**	0.041	2.559**	1.701
	(0.037)	(0.028)	(0.031)	(1.146)	(1.875)
Volatility	0.100*	0.077*	0.061	0.713**	0.459
	(0.058)	(0.046)	(0.042)	(0.307)	(0.314)
Volume	-0.068	0.018	0.099	28.349***	15.239***
	(0.220)	(0.188)	(0.183)	(1.159)	(1.342)
Firm FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Adj. R^2	0.58	0.59	0.54	0.20	0.05

(Table 8 continues on the next page)

(Table 8 continued)

Panel B: Tercile 2					
	Quoted [1]	Effective [2]	EOD [3]	CS [4]	AR [5]
SAD	0.366***	0.198***	0.120***	2.884**	3.108
	(0.045)	(0.032)	(0.024)	(1.227)	(1.992)
Volatility	0.062***	0.042***	0.028***	0.808***	0.434***
	(0.014)	(0.009)	(0.007)	(0.137)	(0.083)
Volume	-0.129**	-0.012	-0.011	27.514***	14.133***
	(0.062)	(0.047)	(0.096)	(1.034)	(1.135)
Firm FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Adj. R^2	0.73	0.74	0.64	0.22	0.05

Panel C: Tercile 3					
	Quoted [1]	Effective [2]	EOD [3]	CS [4]	AR [5]
SAD	0.533***	0.284***	0.242*	4.076***	3.480
	(0.153)	(0.101)	(0.144)	(1.427)	(2.393)
Volatility	0.116***	0.080***	0.091***	0.284*	0.551***
	(0.026)	(0.018)	(0.012)	(0.151)	(0.064)
Volume	-1.630***	-1.068***	-0.832**	28.301***	15.928***
	(0.524)	(0.367)	(0.391)	(1.409)	(1.268)
Firm FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Adj. R^2	0.66	0.64	0.54	0.25	0.06

Table 9
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 is 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	0.052	0.061	0.035	0.024	0.057
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	0.039	0.019	0.038	0.027	0.045
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 9 continues on the next page)

(Table 9 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	0.041	0.028	0.034	0.025	0.048
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	0.068	0.071	0.053	0.293	0.079
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 10
SAD and International Low-Frequency Liquidity Metrics

The table examines, from an international perspective, the relation between the SAD Incidence 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:

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

where *DepVar* is one of the three above-mentioned low-frequency metrics in stock i on day t, *SAD* is the SAD Incidence variable, *Volume* is the lagged natural logarithm of daily number of shares traded, and *Volatility* is computed as the the difference between the high and low prices of the day scaled by their average and multiplied by 100. 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	0.177	2.163***	2.420**
	(0.907)	(0.443)	(1.015)
Volume	-0.576***	-0.181***	-0.292***
	(0.014)	(0.010)	(0.011)
Volatility	0.356***	0.350***	0.361***
	(0.010)	(0.009)	(0.010)
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	0.598	-0.447	-0.871
	(0.411)	(0.630)	(1.590)
Volume	-0.276***	-0.005	-0.067***
	(0.017)	(0.020)	(0.022)
Volatility	0.090***	0.226***	0.221***
	(0.012)	(0.016)	(0.018)
Firm FE	Y	Y	Y
Year FE	Y	Y	Y
N (millions)	15.2	9.7	8.4
Adj. R^2	0.487	0.43	0.33

(Table 10 continues on the next page)

(Table 10 continued)

Panel C: Tropics (Between 23.5° N and 23.5° S)			
	EOD [1]	CS [2]	AR [3]
SAD	-1.184	-1.784**	1.510
	(1.065)	(0.693)	(1.125)
Volume	-0.402***	-0.129***	-0.232***
	(0.030)	(0.019)	(0.020)
Volatility	0.254***	0.340***	0.330***
	(0.041)	(0.028)	(0.031)
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	15.267***	5.221***	6.605***
	(1.772)	(0.958)	(1.307)
Volume	-0.705***	-0.373***	-0.376***
	(0.019)	(0.015)	(0.015)
Volatility	0.494***	0.587***	0.518***
	(0.014)	(0.013)	(0.012)
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

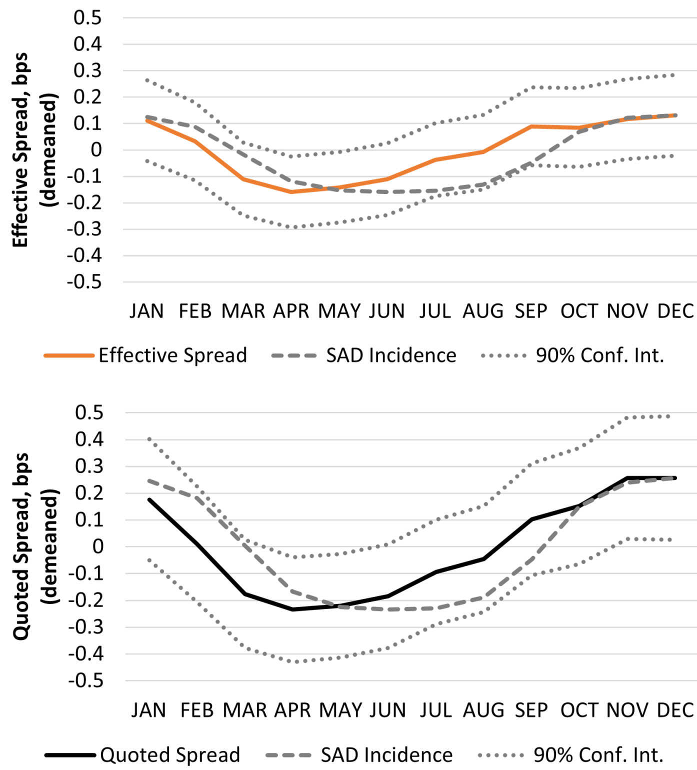

Figure 1
SAD and liquidity costs: effective and quoted spreads

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 Incidence (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. All series have been demeaned for ease of comparison across plots. Dotted lines represent a 90% confidence interval around the spread.

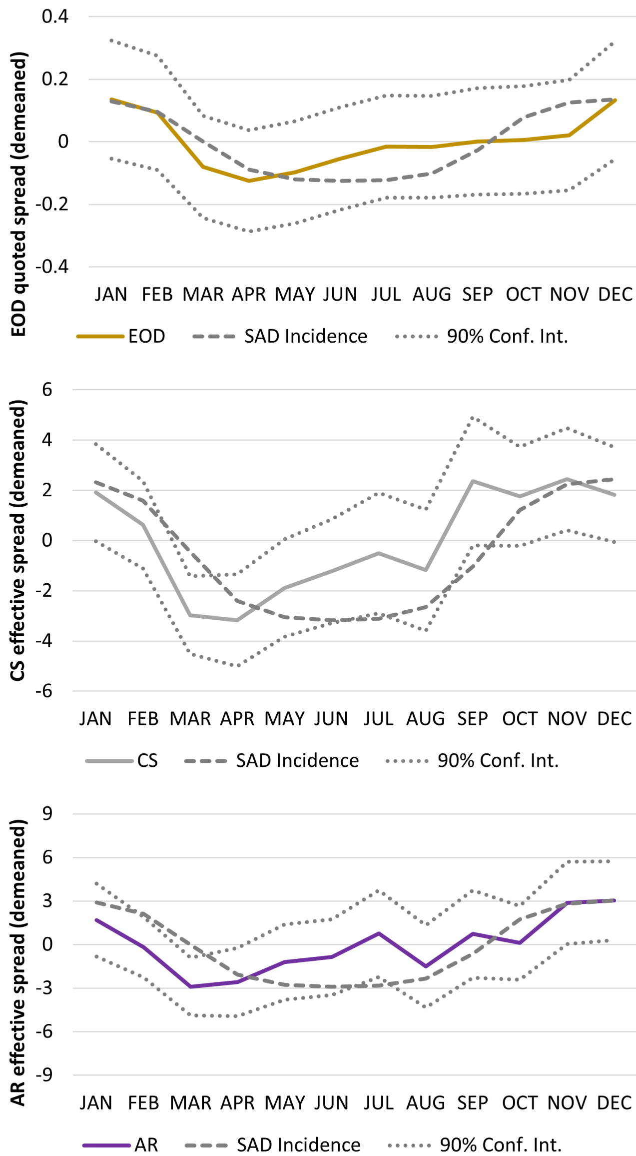

Figure 2
SAD and low-frequency liquidity metrics

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 Incidence (long-dashed line) for the sample period staring in January 2010 through December 2019. The spread measures are three-month centered moving averages. 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